Agent Based Modeling and Simulation Framework

For Supply Chain Risk Management

DISSERTATION

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FOR SUPPLY CHAIN RISK MANAGEMENT

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Abstract

This research develops a flexible agent based modeling and simulation (ABMS) framework for supply chain risk management with significant enhancements to standard ABMS methods integrated with software agents and extended supply chain risk modeling. Our framework provides Air Force Materiel Command (AFMC) with a scalable modeling approach to more efficiently capture supply chain performance and risks. We begin with the use of software agents to gather and process input data for use in our simulation model. For our simulation model we extend an existing mathematical framework for discrete event simulation (DES) to ABMS and then implement the concepts of variable resolution modeling from the DES domain to ABMS and provide further guidelines for aggregation and disaggregation of supply chain models. Existing supply chain risk management research focuses on consumable item supply chains. Since the AF supply chain contains many reparable items, we fill this gap with our risk metrics framework designed specifically for the greater complexity of reparable item supply chains. We present new metrics along with existing metrics, in a framework for reparable item supply chain risk management and discuss aggregation and disaggregation of metrics for use with our variable resolution modeling.

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FOR SUPPLY CHAIN RISK MANAGEMENT

1 Introduction

1.1 General Discussion

This document presents a framework for supply chain risk management, with focus on reparable item supply chains. The framework is comprised of software agents, agent based modeling and simulation (ABMS) and a risk measurement framework. Software agents gather and analyze data from databases, or from the internet, to provide input for the agent based simulation. The agent based model simulates supply chain dynamics and the output from the simulation is used to compute supply chain performance and risk metrics. Finally, a backend to the simulation displays these metrics for use by management and decision making officials. The goal of this research is to develop smaller, but integrated, contributions within the supply chain risk management area of research.

The framework can be used to assess risk mitigation strategies or to recurrently assess risk and supply chain performance. Software agents can periodically (i.e. daily/weekly/etc.) collect and analyze data, then run simulations, and finally display current (and past) performance and risk metrics. This technique could provide information about a risk event occurring instantaneously or events leading up to a supply

chain problem. To determine how to prevent a problem or determine what to do after a problem occurs, the framework can be used to analyze effectiveness of several risk mitigation strategies.

The methodology is applied to a selected portion of the United States Air Force (AF) supply chain, namely, a small portion of the F16 supply chain, but the general framework can theoretically be applied to any reparable item supply chain. The USAF supply chain contains numerous weapons systems, inventory parts, depots, bases, Forward Operating Bases (FOBs), maintenance personnel, project managers, logistics personnel, databases, and supplies distributed globally. Furthermore, the USAF has several budgetary constraints and also interacts and shares some resources with other branches of the Department of Defense (DoD). DoD has emphasized the concern of security threats due to supply chain disruptions in a new policy called “National Strategy for Global Supply Chain Security (Heilprin 2012).”

In the most simplistic view, when a part on an aircraft fails it is repaired at the base level, which includes the flightline and backshops. If the part cannot be repaired at the base, due to personnel capacity and/or equipment constraints, the part is shipped to a depot. Depots are comprised of several specialty shops that are better equipped to repair broken parts. If the depot cannot repair a part, then a new part can be ordered from the original equipment manufacturer. This process depiction is very simplistic in that it does not consider factors, such as: parts are sent between bases, i.e. lateral supply; parts are taken from one aircraft to quickly satisfy the needs of another aircraft, known as cannibalization; modularization, where if one part of the module fails the entire module must be replaced; not all parts are repaired, and; there are scheduled repairs and random

failures. Furthermore, there is an extraordinary amount of paperwork, administrative work, and data tracking within the supply chain.

1.2 Motivation

Military logistics suffer from large complexity and scope because there are: millions of different object types to be managed; tens of thousands of different interleaved discrete business processes; thousands of different organizations with their own physical plants, user requirements, and constraints; a complex, continual interplay between planning and execution; and over a thousand legacy databases and systems with different data models and protocols (BBN 2004). Similar characteristics also apply to many large commercial/industry supply chains, such as Caterpillar, Wal-Mart, etc.

Along with these logistical challenges, companies must deal with ever diminishing funding and greater threats of terrorism. Commercial companies also face increased competition from globalization, while the military must deal with changing military presence in the Middle East and other areas around the world. Therefore, companies and military organizations constantly face greater needs for supply chain risk management. The research presented in this document aims to provide the methodology framework to support this need.

The primary goal of this research is the development of a better supply chain risk management framework, comprised of smaller, but integrated, research contributions. The intermediate goals are the integration of software agents with an agent based simulation platform, development of agent design guidelines for handling varying levels

of fidelity, and development of a supply chain risk metrics framework for reparable item supply chains.

Integration of software agents with an agent based platform provides a dynamic and more intuitive method for simulating supply chains. Existing agent based simulation software reduces the time and effort of modeling a supply chain, by providing preprogrammed modules. That is, code has already been written by software developers to perform standard supply chain entity tasks, such as check inventory level. By linking software agents with an agent based platform, the effort to develop and code simulation agents is reduced. Guidelines for designing agent structure and interactions to accommodate scalability reduce the time and effort required when adapting existing agent based simulation models for use beyond their original purpose. Similar guidelines for developing and scaling risk metrics complete our framework. With this approach agent based simulation models can be used for multiple studies without starting from scratch every time.

1.3 Proposed Research Contributions

The overall contribution is a better supply chain risk management framework, which is divided into three smaller contributions:

- Integration of software agents with agent based modeling and simulation (ABMS) agents
    - software agents performing data mining to produce inputs for agent based simulation

- ABMS guidelines for aggregation / disaggregation of supply chain agents and interactions
    - Designing agent structure to allow for easy scalability in terms of fidelity
- Supply chain risk metrics framework for reparable item supply chains
    - Selectable and scalable in terms of fidelity

1.4 Organization of Dissertation

The remainder of this research encompasses six chapters. The second chapter provides a literature review of supply chain risk management, software agents, agent based modeling and simulation and supply chain risk measurements and metrics. Chapter three provides the simulation framework that integrates software agents, ABMS, and risk metrics for management of supply chain risk. Chapter four outlines the agent structure and guidelines for designing ABMS for aggregation and disaggregation. Chapter five provides a risk measurement framework for reparable item supply chains. Chapter six presents the application of the proposed ABMS and risk management framework to a portion of the F-16 supply chain. Finally, the last chapter summarizes the presented research and future avenues of related research.

2 Literature Review

2.1 Overview

This literature review is comprised of four main literature areas: supply chain risk management, software agents, agent based modeling and simulation (ABMS), and supply chain risk measurement.

2.2 Supply Chain Risk Management

Risk is defined by Juttner et al. (2003) as “the variation in the distribution of possible supply chain outcomes, their likelihood, and their subjective values.” Risk management is the process of examining all possible outcomes and weighing the potential returns against the potential risks of the investment (Pettit et al. 2010). Supply chain risk management grew in popularity as a result of catastrophic events, such as the terrorist attacks on the World Trade Center in 2001, Hurricane Katrina in 2005 and the SARS epidemic in South-East Asia in 2003 (Wagner and Bode 2006). Some examples where the lack of, or poor, risk management led to negative company impacts include: a fire caused by lightning in a semiconductor plant leading to over $400 million in lost revenue for the Ericsson company; Nike’s decrease in market capitalization by almost 20% and lost revenue of $100 million due to difficulties implementing supply chain management software; and the massive tire recalls and over 100 highway fatalities resulting from quality problems with Firestone tires (Shi 2004).

Factors contributing to the increased vulnerability of supply chains include globalization of supply chains, increased outsourcing, technological innovations,

increased volatility of demand, increased demand for product availability, customization, low prices, specialized factories, centralized distribution, shortening product life cycles, and Just-In-Time's lean inventory practices, which lead to little or no inventory and few suppliers (Foroughi et al. 2006; Pettit et al. 2010). Specifically for transportation operations, the main drivers of risk are delays, delivery constraints, lack of coordination, variable demand and poor information (Sanchez-Rodriguez et al. 2010).

Risk analysis is classified, by Pai et al. (2003), into three categories: vulnerability assessment, which consists of threat-asset identification and susceptibility; consequence analysis, and; countermeasure analysis and implementation. These categories align with the basic steps of supply chain risk management outlined by Tuncel and Alpan (2010):

1. Risk Identification
2. Risk Assessment
3. Risk Management
4. Risk Monitoring

2.2.1 ***Types of Risk.***

There is a vast amount of literature on supply chain risk and categorizations of supply chain risk. Most literature lists risks according to a categorization/classification framework. The most recurrent classification schema observed from literature divides supply chain risk into supply, demand, and environmental. Table 1 lists other supply chain risk classifications and Table 2 lists the supply chain risks that fall within these classifications. With respect to the Air Force (AF) supply chain the classification from Table 1 that fits most naturally is strategic, tactical, and operational risks. This

classification aligns with military language. However, a subdivision that should be included in an AF supply chain risk classification is security risks.

Table 1 - Supply Chain Risk Classifications

Risk Classification	Source
demand-side, supply-side, and catastrophic	(Wagner and Bode 2006)
quantitative and qualitative	(Svensson 2000)
supply, demand, and environmental	(Juttner et al. 2003)
disruptions, delays, systems, forecast, intellectual property, procurement, receivables, inventory, and capacity	(Chopra and Sodhi 2004), (Adhitya et al. 2009)
strategic, tactical, and operational	(Ritchie and Brindley 2007) (Gunasekaran et al. 2001)
supply co-ordination and supply disruption	(Kleindorfer and Wassenhove 2004)
probability and importance	(Hunter et al. 2004)
origin from capacity limitation, technology incompatibility, supply disruptions, currency fluctuations and disasters	(Zeng et al. 2005)
endogenous uncertainty and exogenous uncertainty	(Trkman and McCormack 2009)
self, cooperation, and system	(Yongsheng and Kun 2009)
environmental, industry, and disruptions	(Houshyar et al. 2010)
supply, operational, demand, and security	(Manuj and Mentzer 2008)
internal and external	(Wu et al. 2006)
environmental, financial, competition, co-operation, and systemic	(Li et al. 2010)
supply, demand, operational, and security	(Christopher and Peck 2004)
macroeconomic, policy, competition, and resource	(Ghoshal 1987)
value chain, operational, event, and recurring	(Shi 2004)
environmental, network-related, and organizational	(Juttner et al. 2003)
material flow, information flow, cash flow, partner relationship	(Xiaohui et al. 2006)
logistics, inventory, organizing, competitive, cooperative, morality, credit, cultural, information transfer, information technology, safety	(Yan et al. 2008)

Table 2 - Supply Chain Risks

Risks	Source
terrorist attacks	(Trkman and McCormack 2009) (Foroughi et al. 2006) (Sanchez-Rodrigues et al. 2010)
contagious disease	(Trkman and McCormack 2009) (Sanchez-Rodriguez et al. 2010)
labor strikes	(Trkman and McCormack 2009)
inflation rate	(Trkman and McCormack 2009)
consumer price index changes	(Trkman and McCormack 2009)
market turbulence	(Trkman and McCormack 2009) (Yongsheng and Kun 2009) (Houshyar et al. 2010) (Li et al. 2010)
technological turbulence	(Trkman and McCormack 2009) (Yongsheng and Kun 2009)
natural disasters (hurricanes, tornadoes, earthquakes, floods, fires, snow/ice storms, and tsunamis)	(Trkman and McCormack 2009) (Yongsheng and Kun 2009) (Houshyar et al. 2010) (Foroughi et al. 2006)

Risks	Source
political turbulence	(Trkman and McCormack 2009) (Yongsheng and Kun 2009) (Houshyar et al. 2010) (Li et al. 2010)
transportation uncertainties	(Wilson 2007) (Wu and Olson 2008) (Foroughi et al. 2006)
competition	(Trkman and McCormack 2009) (Houshyar et al. 2010)
storage transfer	(Yongsheng and Kun 2009)
moral risk	(Yongsheng and Kun 2009)
culture difference	(Yongsheng and Kun 2009)
information system	(Yongsheng and Kun 2009)
equipment transfer	(Yongsheng and Kun 2009)
economic crisis	(Yongsheng and Kun 2009)
financial risk (not meeting certain target profit or exceeding a cost level)	(Sabio et al. 2010)
social uncertainties	(Houshyar et al. 2010) (Li et al. 2010)
exchange rates	(Foroughi et al. 2006)
port lockouts	(Foroughi et al. 2006)
materials shortages	(Foroughi et al. 2006)
power outages	(Foroughi et al. 2006)
regulations	(Li et al. 2010) (Sanchez-Rodrigues et al. 2010)
quality issues	(Sanchez-Rodriguez et al. 2010)

One of the most prevalent supply chain risks for the AF is port lockouts (or border lockouts), since this has happened several times with transporting supplies into Afghanistan. Other risks that highly pertain to the AF supply chain are terrorist attacks and natural disasters. The military is often called in to provide assistance during and after disasters, which can disrupt the AF supply chain. Other risks directly related to the AF supply chain include equipment transfer, transportation uncertainties, and information systems.

2.2.2 ***Risk Mitigation Strategies.***

According to Tang (2006) the four basic approaches for managing supply chain risks are supply management, product management, demand management, and information management. Following this categorization, supply chain risk mitigation strategies are listed in Table 3.

Table 3 – Supply Chain Risk Mitigation Strategies

Risk Mitigation Strategy	Source
Supply Management	
postponement	(Tang 2006) (Manuj and Mentzer 2008)
strategic stock investment	(Tang 2006) (Chopra and Sodhi 2004) (Khan and Burnes 2007)
flexible supply base	(Tang 2006) (Rice and Caniato 2003) (Ponomarov and Holcomb 2009) (Xiaohui et al. 2006)
economic supply incentives	(Tang 2006)
multi-modal flexible transportation	(Tang 2006) (Pettit et al. 2010)
multiple suppliers	(Chopra and Sodhi 2004) (Khan and Burnes 2007) (Wagner and Bode 2006) (Manuj and Mentzer 2008)
redundancy	(Rice and Caniato 2003) (Ponomarov and Holcomb 2009)
economic supply incentives	(Pettit et al. 2010)
make-and-buy	(Pettit et al. 2010)
reduction of uncertainty, complexity, reengineering	(Ponomarov and Holcomb 2009)
add capacity	(Chopra and Sodhi 2004) (Tang 2006) (Manuj and Mentzer 2008)
hedging	(Manuj and Mentzer 2008)
agility	(Christopher and Peck 2004) (Ponomarov and Holcomb 2009)
control/share/transfer risk	(Manuj and Mentzer 2008)
Product Management	
product variety	(Tang 2006)
postponement / product differentiation	(Tang 2006) (Khan and Burnes 2007) (Wanger and Bode 2006) (Manuj and Mentzer 2008)
dynamic assortment planning	(Tang 2006)
Demand Management	
dynamic pricing	(Tang 2006)
dynamic assortment planning	(Tang 2006)
silent product rollover	(Tang 2006)
forecasting / speculation	(Manuj and Mentzer 2008) (Tang 2006)
control/share/transfer risk	(Manuj and Mentzer 2008)
change inventory control mode	(Xiaohui et al. 2006)
Information Management	
information sharing	(Faisal et al. 2006) (Khan and Burnes 2007) (Wagner and Bode 2006) (Manuj and Mentzer 2008) (Xiaohui et al. 2006)
collaboration	(Faisal et al. 2006) (Tang 2006) (Ponomarov and Holcomb 2009)
information security	(Faisal et al. 2006)
visibility / knowledge	(Tang 2006) (Ponomarov and Holcomb 2009) (Faisal et al. 2006)
forecasting	(Tang 2006)
transparency	(Ponomarov and Holcomb 2009)
risk sharing	(Xiaohui et al. 2006) (Faisal et al. 2006) (Manuj and Mentzer 2008)

2.2.3 ***Risk Modeling.***

Pettit et al. (2010) states “the best level of resilience will be achieved only when a balance is maintained between capabilities and vulnerabilities.” This statement, specific to supply chain resilience, is valid for the broader area of supply chain risk management. To determine this balance, supply chain managers must make decisions on site location, choices of production, packaging and distribution lines, and capacity increment or decrement policies (Poojari et al. 2008). Other decisions include resource allocation, network structuring, number of facilities and equipment, number of stages, service sequence, volume, inventory level, size of workforce, and extent of outsourcing (Min and Zhou 2002).

Naraharisetti et al. (2009) divides the above decisions into system representation; modeling and simulation; synthesis and design; planning and scheduling; and control and supervision. Juttner et al. (2003) categorizes the decisions into the following supply chain trade-off decisions: repeatability vs. unpredictability; lowest bidder vs. known supplier; centralization vs. dispersion; collaboration vs. secrecy; redundancy vs. efficiency; and managing risk vs. delivery value. One last trade-off that an enterprise must consider when assessing supply chain risk is whether the enterprise is risk prone or risk averse (Choi et al. 2008).

A large amount of literature describes several modeling techniques that can assist decision makers in making the previously described supply chain decisions. Figure 1 depicts the general supply chain modeling techniques, which can be divided into deterministic models, stochastic models, hybrid models, and IT-driven models (Min and

Zhou 2002). Another largely used technique not mentioned by Min and Zhou (2002) is the vast range of diagramming techniques.

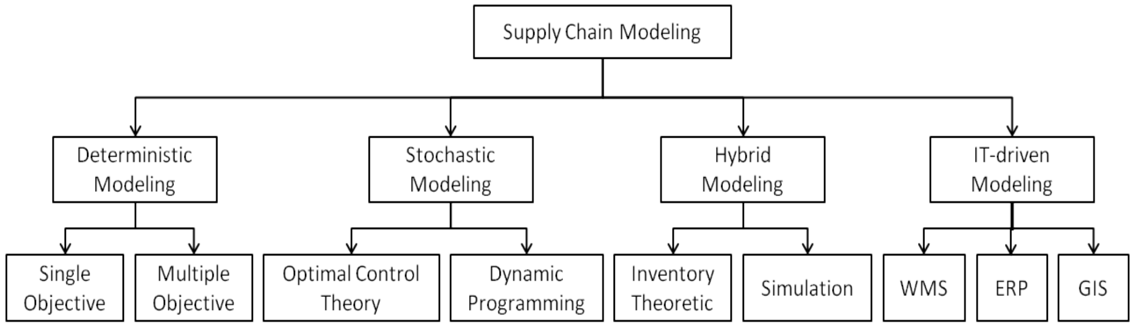


Figure 1 - Taxonomy of Supply Chain Models (Min and Zhou 2002)

Diagramming techniques include graph theory (Wagner and Neshat 2010, and Caridi et al. 2010), process mapping (Shi 2004), critical path analysis (Juttner et al. 2003), causal tree structure (Pai et al. 2003, and Foroughi et al. 2006), value-focused thinking and process chain process modeling (Neiger et al. 2009), and work-flow diagrams (Adhitya et al. 2009).

Simulation models include agent based (Datta et al. 2007, Chen and Huang 2007, and Kroger 2008), discrete event (Kull and Closs 2008, Schmitt and Singh 2009), timed Petri net based simulation (Tuncel and Alpan 2010), and Monte Carlo (White 1995, Wu and Olson 2008, and Schmitt and Singh 2009). More detail on simulation techniques is provided in section 2.3 of this document.

Optimization models include heuristics (Wang and Shu 2007, and Tang et al. 2008), bicriterion mathematical programming (Gaur and Ravindran 2006), chance constrained programming, data envelopment (Gaur and Ravindran 2006), stochastic programming (Snyder et al. 2007, Goh et al. 2007, and Poojari et al. 2008), goal

programming (Kull and Talluri 2008), linear programming (Ahmed et al. 2007, and Bogataj and Bogataj 2007), and lattice-programming (Cucchiella and Gastaldi 2006).

Other techniques used in supply chain modeling include stress testing (Shi 2004); behavioral risk theory (Ellis et al. 2010); complexity analysis (Yang and Yang 2010); structural self-interaction matrix and reachability matrix (Faisal et al. 2006); information entropy assessment (Li et al. 2010); economics models (Kleijnen and Smits 2003, Kirkwood et al. 2005, and Singh et al. 2010); Pareto analysis (Gunasekaran et al. 2001); analytical hierarchy process (AHP) analysis (Bargbarosoglu and Yazgac 2000, and Rabelo et al. 2007); failure mode, effects and criticality analysis (FMECA) technique (Tuncel and Alpan 2010); Bayesian models (Li and Chandra 2007); and principle component analysis (Qiang and Jingjuan 2010).

2.2.4 ***Summary.***

There is a vast amount of literature on consumable item supply chain risk management. However, there is little research focusing on reparable item supply chains, which entail greater complexity than consumable item supply chains. Furthermore, existing modeling techniques lack the dynamic, complexity and stochastic requirements necessary for modeling risk of large supply chains. Supply chains involving reparable items cannot easily be captured with mathematical equations because of redundancy and nonlinear flow of material. Thus, our research fills this gap by employing simulation, with intended application to portions of the AF reparable supply chain. For further information on all aspects of supply chain risk management refer to Tang (2006).

2.3 Software Agents

2.3.1 ***Definitions.***

The Organization for Advancement of Structured Information Standards depicts software agents as “a paradigm for organizing and utilizing distributed capabilities that may be under the control of different ownership domains (Oluwole 2008).” Gilbert (2007) defines a software agent, with respect to computer science, as “a software entity, which is autonomous to accomplish its design objectives, considered as a part of an overall objective, through the axiom of communication and coordination with other agents.” For this research, a software agent is defined as a software program that performs actions in pursuit of a specific goal (Nienaber and Barnard 2007).

A software agent that is self-contained and can move within a network to act on behalf of the user or another entity is called a mobile agent (Pham and Karmouch 1998). Intelligent software agents are innovative programs that perform autonomous and continuous research and data gathering tasks, analyze the results, and deliver personalized, relevant, exploitable information (Agentland 2010). Software agents, multi-agents and intelligent agents are sometimes used synonymously throughout literature.

2.3.2 ***Purpose / Applications.***

In general, software agents are used to emulate enterprise entities (Julka et al. 2002). These entities can be macro, such as a supply chain retailer, or micro, such as a forklift in a warehouse. Some agents serve as monitoring agents that “monitor the states of supply chains by observing specific events and exceptions in real-time and alerting managers if problems occur (Reese 2007).” Software agents can be applied to databases,

networks, virtual domains, computer applications and operating systems (Croft 2004). The types of agents observed in literature include information retrieval agents, advisory agents, data cleansing agents, communication agents, scheduling agents, and negotiation agents.

2.3.3 ***Characteristics.***

The primary characteristics of agents are autonomy, social ability, reactivity and proactiveness. Autonomy is the agent's ability to operate without direct intervention of humans or others, and the agent's control (or semi-control) over its actions and internal state. Social ability of an agent is its capability of interacting with other agents, or humans, via some kind of communication language. Reactivity refers to an agent's ability to perceive its environment and respond in a timely fashion to changes that occur in it. Proactiveness is an agent's ability to exhibit goal-directed behavior by taking the initiative, and not simply acting in response to its environment. (Moyaux et al. 2006)

Additional characteristics that are not defining characteristics of agents include adaptivity and flexibility. Adaptivity refers to an agent's ability to customize itself on the basis of previous experiences (Nienaber and Barnard 2007), while flexibility refers to an agent's ability to dynamically choose which actions to invoke and in what sequence to execute those actions (Pai et al. 2000). The essential characteristics specific to mobile agents are security, portability, mobility, communication, resource management, resource discovery, identification, control and data management (Pham and Karmouch 1998). Table 4 provides a spectrum of seven software agent characteristics, ranging from simple to complex, from left to right.

Table 4 - Spectrum of software agent characteristics (Bui and Lee 1999)

Characteristic	Level of Complexity (Low to High)			
Intelligence	Rigid / automated	Reasoning	Planning	Learning
Mobility	Stationary			Mobile
Lifetime	Adhoc	Cloning		Persistent
Interaction	Agent-to-agent	Agent-to-application		Agent-to-user
Task Specificity	Specific			General
Initiative	Push			Pull
Environment	Stable / secure			Stochastic / insecure

2.3.4 ***Challenges.***

The biggest challenge with using software agents is capturing decision/behavioral logic of agents, and doing so in a timely manner. This challenge is prevalent in most modeling and simulation efforts. As often depicted in simulation literature, modeling is as much an art as it is a science. This may be true for agent based modeling more than discrete event modeling.

Challenges specific to mobile agents include transportation, authentication, secrecy, security, cash, performance, and interoperability/communication/brokering services (Nwana 1996). Software agent developers must consider the following questions in regard to these challenges (Nwana 1996):

- Transportation: how does an agent move from place to place? How does it pick up and move?
- Authentication: how do you ensure the agent is who it says it is, and that it is representing who it claims to be representing? How do you know it has navigated various networks without being infected by a virus?
- Secrecy: how do you ensure that your agents maintain your privacy? How do you ensure someone else does not read your personal agent and execute it for his own

gains? How do you ensure your agent is not killed and its contents 'core-dumped'?

- Security: how do you protect against viruses? How do you prevent an incoming agent from entering an endless loop and consuming all the CPU cycles?
- Cash: how will the agent pay for services? How do you ensure that it does not run amok and run up an outrageous bill on your behalf?
- Performance issues: what would be the effect of having hundreds, thousands or millions of such agents on a WAN?
- Interoperability/communication/brokering services: how do you provide brokering/directory type services for locating engines and/or specific services? How do you execute an agent written in one agent language on an agent engine written in another language? How do you publish or subscribe to services, or support broadcasting necessary for some other coordination approaches?

Several of these challenges have been addressed in literature. Researchers have used public-key and private-key digital signature techniques and limited interpreted languages to prevent illegal instructions from being executed to handle authentication, cash, secrecy and security (Nwana 1996). The Cognitive Agent Architecture (Cougaar) that is discussed in Section 2.3.7 has been developed to overcome some of the software agent challenges. For example, fully automatic monitoring and restart of agents handles the unexpected loss of agents, while automated application maintenance for load balancing prevents performance issues (Helsinger et al. 2005).

2.3.5 ***Software Agents and Data Mining.***

For many companies and organizations, information across all enterprises and the departments is distributed, dynamic and disparate in nature (Julka et al. 2002). This tends to be true for the AF also. For this type of information to be useful the process of data mining must be applied. Data mining is a process that combines tools and techniques from machine learning, statistics, artificial intelligence, and data management to extract useful knowledge from data automatically (Srinivas and Harding 2008).

Software agents provide a natural means for data mining. Applications of software agents for data mining extend to Aerospace manufacturing industry (Oluwole 2008), electrical transformers (Wu et al. 2004), ERP systems (Symeonidis et al. 2003), shop floor control (Srinivas and Harding 2008), etc. Examples of agent enhancements for data mining include implementation of data clustering algorithms in agent logic to protect company privacy (da Silva et al. 2006), aggregation of domain context in agent data analysis logic (Xiang 2008), and learning algorithms for continuous data mining (Srinivas and Harding 2008). For more literature pertaining to software agents for data mining and preprocessing refer to Othman et al. (2007).

2.3.6 ***Decision Support Systems and Modeling with Software Agents.***

Decision centers in present-day enterprises often reside in different departments (Julka et al. 2002). Because of this, agents are ideal for collecting information from each department and performing enterprise-wide analysis to aid decision making.

Software agents have been implemented in areas such as manufacturing, process control, telecommunications, air-traffic control, transportation systems, information

management, electronic commerce, business process management, patient monitoring and rescue team management (Moyaux et al. 2006). Other application areas include chemical industries (Garcia-Flores et al. 2000), produce transport (Jedermann et al. 2006), and environmental health (Sokolova and Fernandez-Caballero 2009). Since the first attempt to model the supply chain through intelligent agents by Fox et al. (1993), there have been several research contributions to supply chain management (refer to Table 5.)

Table 5 - Summary of intelligent agent applications in supply chain management (Caridi et al. 2005)

Research Feature	Literature Contribution
Information sharing	(Baumgaertel et al. 1998)
	(Chandra et al. 2001)
	(Hinkkanen et al. 1999)
	(Strader et al. 1998)
	(Verdicchio and Colombetti 2002)
Bullwhip management	(Kimbrough et al. 2001)
	(Yang and Yang 1990)
Supply-chain integration	(Fox et al. 1993)
	(Gjerdrum et al. 2001)
	(Sherhory and Kraus 1998)
	(Swaminathan et al. 1998)
	(Fu et al. 2000)
Exception handling	(Beck and Fox 1994)
	(Fox et al. 2000)
Negotiation	(Chen et al. 1999)
	(Walsh and Wellman 2000)
	(Qinghe et al. 2001)
	(Shen et al. 1990)

More recent innovations to software agent technology for supply chain management include the integration of RFID with mobile agents to track freshness of produce in transit (Jedermann et al. 2006), integration of numerous multi-agent systems (Frey et al. 2003), adaptation of fuzzy logic to agent behavior (Si and Lou 2009), integration of multi-agent technology and constraint network (Wu 2001) and integrating

object-oriented modeling of supply chain flows with agent-oriented modeling of supply chain entities (Julka et al. 2002).

Zimmermann et al. (2006) developed a decision support system for supply chain event management. They developed a simulator agent that facilitates simulation of orders in a supply chain, but the simulation was performed by a database. Sokolova and Fernandez-Caballero (2009) also use a simulation agent, but is accomplished with equations instead of a database. A diagram of the decision support system by Sokolova and Fernandez-Caballero (2009) is provided in Appendix A.

Instead of a simulator agent, we propose the use of software agents interacting with agent based simulation agents. That is, use an entirely separate software platform to simulate the supply chain. Further details are discussed in the methodology section of this paper.

2.3.7 ***Cougaar.***

Cougaar (Cognitive Agent Architecture) is an open-source Java-based multi-agent architecture that provides a survivable base on which to deploy large-scale, robust distributed applications (Helsinger et al. 2005, Upal and Fung 2003). Cougaar was developed for the US Defense Advanced Research Projects Agency (DARPA) under the Advanced Logistics Program (ALP) (BBN 2004), with the goal to explore the potential of distributed multi-agent systems for military logistics (Helsinger et al. 2005). The architecture was developed by ALPINE, a consortium composed entirely of BBN Technologies, over a period from 1996 to 2001 (BBN 2004).

Under a new DARPA program, Ultra-Log, BBN continued to develop and maintain Cougaar from 2001 to 2004 (BBN 2004). Ultra-Log focused on enhancing Cougaar by installing components offering robustness, security, and scalability (BBN 2004). Upal and Fung (2003) enhanced the architecture by adding dynamic plan evaluation capability to Cougaar that essentially evaluates and chooses the best course of action in an uncertain situation when multiple plans are available.

The US Army has included Cougaar as a central design point in a new logistics decision support system, and a military maneuver decision support system (Helsinger et al. 2005). Furthermore, CougaarME, Cougaar tuned to small devices, was used by one program to control semi-autonomous robots over a wireless ad-hoc network (Helsinger et al. 2005).

2.3.8 ***Summary.***

Literature on software agents depicts their usefulness in decision support tools, and specifically data mining. Although there are several agent design issues that must be considered, software agents provide a great mechanism for data mining AF databases for useful information to aid supply chain risk management. However, literature on software agent decision support tools does not depict a natural and easily developable modeling technique necessary for modeling the AF supply chain. Thus, our research fills this gap by integrating data mining software agents with an agent based simulation software platform.

Most AB simulation platforms contain pre-coded logic and functions, such as event handling and message passing, which reduce model development time. To aid

collection and analysis of simulation output, most simulation platforms have built-in charts and tables that can export data in several formats. Developing an AB simulation using software agents, known as multi-agent simulation, requires extensive coding and linking with data structures to achieve the capabilities of a software platform. Thus, our framework uses the benefits of SA's in data mining with the benefits of AB simulation software platforms to achieve a better risk management framework.

2.4 Agent Based Modeling and Simulation

Agent based modeling and simulation (ABMS) characterizes a system by allowing individual agents to perform a set of behavior rules, which leads to interactions between agents and between agents and their environment. This method of simulation is "founded on the notion that the whole of many systems or organizations is greater than the simple sum of their constituent parts (North and Macal 2007a)." ABMS combines discrete event simulation, which provides the interactions of individual components within a simulation, and object-oriented programming, which provides well-tested frameworks for organizing agents based on their behaviors (North and Macal 2007a).

Agents are defined by Pan et al. (2009) as "active, persistent (software) components with the abilities of perceiving, reasoning, acting and communicating." Having sets of attributes and behavior rules, agents are essentially the decision making components in complex adaptive systems (North and Macal 2007a). While attributes describe the agent, the behavior rules dictate how agents respond to their environment and other agents, which leads to emergent behavior of the entire system.

ABMS originated from the study of complex adaptive systems and cellular automata, with some of the earliest agent based models being “Game of Life” and sugarscape models (North and Macal 2007a). For more details on the history of ABMS refer to (Heath 2010).

2.4.1 *ABMS for Supply Chains.*

ABMS is highly germane to supply chain management because performance measures, such as productivity, shipping accuracy, and inventory can be predicted via a model prior to expending money and time on changing the actual system. Furthermore, enterprises in a supply chain (e.g. manufacturer, wholesaler, etc.) have a natural translation to agents. By adequately capturing the behavior rules of each enterprise, an agent based model can be used to observe interactions between the enterprises and system performance can be derived from emergent system patterns.

According to Amouzegar et al. (2008) “agent based models are already in wide use within the DoD for force-on-force simulations but have only recently been adapted for military logistics use.” Some simple supply chain simulations for logistics have been done, but almost none have modeled actual organizations with sufficient detail to adequately compare alternative policies (Amouzegar et al. 2008). This is due to the complexity of the disparate, decentralized organizations that make up the Air Force supply chain. One initiative that demonstrates the utility of agents for military logistics is the Coalition Agent eXperiment (CoAX), led by the Defense Advanced Research Projects Agency (DARPA) (Amouzegar et al. 2008). From this initiative it became

apparent that the following technological and social issues must be overcome for agents to effectively be implemented for military logistics planning:

- Technological issues: logistics business process modeling, protocols, ontologies, automated information-gathering, and security
- Social issues: trusting agents to do business for you, accountability and the law, humans and agents working together, efficiency metrics, ease of use, adjustable autonomy, adjustable visibility, and social acceptability versus optimality (Amouzegar et al. 2008)

DARPA has also been working on an end-to-end logistics model under the Advance Logistics Project, which was extended to the Ultra-Log project (Amouzegar et al. 2008). As part of the Ultra-Log project, an agent based model was developed to show how various supply-chain network topologies fare under attack (Thadakamalla et al. 2004). The model, built in Netlogo, was originally developed to analyze military supply chain vulnerability to terrorist or military attacks (Thadakamalla et al. 2004).

For further information on ABMS for supply chains refer to (Jirong et al. 2008) and (Sirivunnabood and Kumara 2009), both of which provide brief literature reviews.

2.4.2 *ABMS for Inventory Control.*

To provide a general overview of the applicability of ABMS specifically for inventory control, this section summarizes several articles on ABMS relevant to inventory control. This section is not meant to be an exhaustive literature review, but

rather provide several examples of recent research in the area of ABMS for inventory control.

Ito and Abadi propose an agent based model for a warehouse system composed of three subsystems; agent based communication system, agent based material handling system, and agent based inventory planning and control system. Warehouse systems take care of fluctuation and uncertainty of demands from customers, and provide just-in-time delivery of materials. That is because inventory avoids shortages, but at the cost of capital investment, operation and maintenance, material handling, and insurance. The model, written in Java, utilizes master agents and subagents including customer, supplier, order, inventory, product, supplier-order, and automatic-guided vehicle (AGV) agents. With further study proposed by the authors, the model will provide a mechanism for autonomous setting of parameters to determine the order points or order-up-to-level point of products based on the history of customer orders and supplier lead times. Furthermore, the model will provide a mechanism for effective job-allocation to AGVs and scheduling jobs of each AGV. (Ito and Abadi 2002)

Li and Li consider a multi-location inventory system with several retailers who share one supplier. The model, built using the Anylogic software, considers demand lead-time, replenishment lead-time, and transshipment lead-time. Also the model does not employ a central agency to decide transshipments, and retailers make their decisions separately. Running the model led to emergent transshipments happening between retailers when in-hand inventory and pipeline stock are not enough to meet the demand. Furthermore, optimal inventory policies were found by considering holding, ordering, transshipment, backorder, and transshipment benefit costs. (Li and Li 2008)

Chen, Zhou, and Hu propose an agent-oriented Petri net model for an inventory-scheduling model, with focus on the problems of analysis and modeling of multi-agent systems. Petri net aims at researching the organization structure and dynamic behavior of a system, with an eye on all possible state changes and the relation of the change in the system. The proposed agent-oriented Petri net model is applied in modeling the inventory scheduling of supply system. (Chen et al. 2008)

Jirong et al. propose a 4-level multi-agent system model for supply chain inventory with a decision-making model for every enterprise agent in the supply chain. This modeling technique was selected due to the dynamic nonlinear complexity of supply chain inventory systems. The simulation study is conducted for the influence of lead time and information sharing among the four agent types; retailer, wholesaler, distributor, and manufacturer. Results confirmed that the information sharing strategy effectively decreases the variation amplitudes of inventory of each enterprise in the supply chain. That is, the bullwhip effect is diminished when enterprises in the supply chain share information. (Jirong et al. 2008)

Jiang and Sheng propose a reinforcement learning algorithm combined with case-base reasoning in a multi-agent supply chain system. Reinforcement learning is an approach to machine intelligence that learns to achieve the given goal by trial-and-error iterations with its environment. This is done by combining dynamic programming and supervised learning. Recent research in this area tends to focus on mathematical or analytical models, such as Bayesian approach, Utility Function Method, fuzzy set concepts and autoregressive and Integrated Moving Average and Generalized Autoregressive Conditional Heteroscedasticity. The multi-agent simulation proposed in

the article was programmed under Java2 Development Kit (JDK) 1.5 to study the problem of dynamic inventory control for satisfying target service level in supply chain with nonstationary customer demand. (Jiang and Sheng 2009)

Cao et al. describe a simulation-based inventory management tool developed for the IBM Enterprise Server Group. IBM's supply chain involves expensive components with high inventory carrying cost, extensive tests for components for high quality requirements, multi-tier suppliers with long lead time, and high customer service levels requiring complex product configuration and quick order response time. The fabrication stage is a build-to-plan process, while the fulfillment stage is a make-to-order process. Thus, the stages together form a hybrid process structure combined with inherent randomness in the process that pose tremendous challenges to inventory management, particularly in terms of financial and operational impacts. To model impact of randomness in parameters like lead times, yields and component usage rates, the authors developed a simulation tool with Java. With inventory costs and Days-of-Supply profiles as outputs, the simulation tool provides decision support at an operational level. That is, the model provides the capability to project the future inventory performance for selected high-dollar parts in IBM Enterprise Server Manufacturing. (Cao et al. 2003)

Sirivunnabood and Kumara used an agent based simulation model to determine appropriate risk mitigation strategies for a supply chain network under supplier risks. Implemented in Java on the Java Agent Development (JADE) platform, the model consists of supplier agents, plant agents, warehouse agents, customer agents, and a controller agent. Unexpected events were randomly generated to mimic the risks that possibly occur in the supply chain. Having a redundant supplier and reserving more

inventories were the two risk mitigation strategies tested for four types of risks, which were depicted by frequency and duration. (Sirivunnabood and Kumara 2009)

Krishnamurthy et al. consider a new inventory control technique for large-scale supply chains, which considers stochastic transport delays, manufacturing times, and repair times and probabilistic characterization of part repair success. Because stochastic disturbances enter at both ends of a bidirectional supply chain and the necessity for overly simplified assumptions, optimization techniques for inventory control for bidirectional stochastic supply chains are computationally intractable. For this reason the paper provides an agent based simulation model of aircraft supply chain involving multiple original equipment manufacturers (OEMs), depots, bases, squadrons, and planes. ABMS was used to avoid explicitly modeling inventory dynamics for each site and formulating complex coupling signals between the sites. With an adaptive feature, the model can adjust stock levels with the objective of reducing excess inventory and maintaining or increasing mission capability of aircraft. The simulation was written in Python language. Output from the model can be used to determine the number of parts of each part type that each site should order from its associated supplier site, and the number of parts of each part type to start manufacturing. (Krishnamurthy et al. 2008)

While ABMS is applicable to supply chains, as depicted in this section and the previous section, there must be consideration of efficiency in implementing ABMS for large supply chains. For ABMS to be truly helpful in analyzing large supply chains there must be a wide range of fidelity within a single model to analyze questions at different managerial levels. To avoid creating new simulation models for every question of

interest, it is recommended to instill the concept of variable resolution in developing agent based simulation models.

2.4.3 *Variable Resolution Modeling.*

Variable resolution modeling is defined by Davis and Hillestad (1993) as "building new models or model families so that users can change readily the resolution at which phenomena are treated." Seamless design refers to designing models such that change in resolution occurs with (a) smooth consistency of representation and (b) consistency of prediction (Davis and Hillestad 1993). In other words, when "zooming" within a model there are no mental disruptions and there is some confidence that the results are consistent (Davis and Hillestad 1993).

When modeling, resolution can refer to entities, attributes, logical dependency, processes, spatial orientation, or temporal orientation. Table 6 provides military examples of how these six aspects of a model may change with levels of resolution.

Table 6 - Aspects of Resolution (Davis and Hillestad 1993)

Aspect of Resolution	Level of Resolution	
	Low	High
Entity	Companies	Battalions
Attribute	Net firepower strength	Number of each weapon system
Logical-dependency	Standard formation	Circumstantial formation
Process	Allocate attrition evenly among battalions on the front line	Compute combat attrition at battalion level based on battle situation
Spatial	Miles	Feet
Temporal	Days	Minutes

Low resolutions models are used for initial cuts, comprehension, systems analysis and policy analysis, decision support, adaptability, low cost and rapid analysis, and making use of low-resolution knowledge and data (Davis and Hillestad 1993). High resolution models are used in understanding phenomena, representing knowledge,

simulating reality, calibrating or informing lower-resolution models, and making use of high-resolution knowledge and data (Davis and Hillestad 1993).

Three principal approaches can be used to achieve variable resolution modeling, namely, selected viewing, alternative sub models (or model families), and integrated hierarchical variable resolution (IHVR) (Davis and Hillestad 1993). Selected viewing uses the one high resolution model and simply hides logic for low resolution models. The alternative sub models approach consists of different models for levels of resolution and users merely switch to the model corresponding to the desirable level of resolution. IHVR refers to modeling that describes critical processes as being composed hierarchically of subordinate processes and resolution changes by replacing higher-level processes with an approximation, or trivial process, depicted by lookup tables (Davis and Hillestad 1993).

2.4.4 ***Summary.***

Literature provided in this section demonstrates the natural fit of agent based modeling and simulation for modeling supply chains. Our research extends the agent based model presented in Krishnamurthy et al. (2008), with addition of other types of agents and more output measures. In addition, our research includes the development of guidelines for aggregation / disaggregation of supply chain agents and interactions to allow for easy scalability in terms of fidelity to fit the needs of the analysis. While the work done on variable resolution modeling is a generalization for any modeling technique, the guidelines are specific for development of agent based models. The primary difference between discrete event variable resolution and AB variable resolution

is the complexity of message passing and agent processes / methods. Thus our research extends the concepts of variable resolution modeling to ABMS.

2.5 Supply Chain Risk Measurements and Metrics

Sink and Tuttle (1989) claim that you cannot manage what you cannot measure. Parker (2000) expands on this statement with the following purposes of measuring organizational performance: identify success; identify whether customer needs are met; help the organization to understand its processes and to confirm what they know or reveal what they do not know; identify where problems, bottlenecks, waste, etc. exist and where improvements are necessary; ensure decisions are based on facts, not on supposition, emotion, faith or intuition; and show if improvements planned actually happened.

2.5.1 *Performance Measures.*

A performance measurement can be defined as “a set of metrics used to quantify the efficiency and/or effectiveness of an action (Neely et al. 1995).” A metric “refers to definition of the measure, how it will be calculated, who will be carrying out the calculation, and from where the data will be obtained (Neely et al. 1995).” Table 7 provides several performance measurement categories in logistics and supply chain, and Table 8 provides several supply chain metrics that are found in those measurement frameworks. For listing of literature on each performance measurement from Table 7 refer to Gunasekaran and Kobu (2007).

Table 7 - Categories of performance measurement in logistics and supply chain systems (Gunasekaran and Kobu 2007)

Key references	Criteria	Details
Kaplan and Norton (1997)	Balanced score card perspective	• Financial • Internal process • Innovation and improvement • Customers
Beamon (1999)	Components of performance measures	• Time • Resource Utilization • Output • Flexibility
Gunasekaran et al. (2001)	Location of measures in supply chain links	• Planning and Product Design • Supplier • Production • Delivery • Customer
Gunasekaran et al. (2001)	Decision-making levels	• Strategic • Tactical • Operational
Financial base (De Toni and Tonchia 2001)	Nature of measures	• Financial • Non-financial
Gunasekaran et al. (2001)	Measurement base	• Quantitative • Non-quantitative
Bagchi (1996)	Traditional vs. modern measures	• Function-based • Value-based

The AF logistics community uses the balanced scorecard perspective, but has modified the perspectives from Customer, Processes, Finance, and Learning and Growth to be Warfighter, Logistics Processes, Resource Planning, and Innovation and Learning (JDMAG 2010). Along with the balanced scorecard, another performance measurement category from Table 7 that aligns well with the AF is the decision-making levels, i.e. strategic, tactical and operational.

2.5.2 *Industry / Commercial Metrics.*

Table 8 - Supply Chain Performance and Risk Metrics

Metrics	Source
Value-at-Risk (VAR)	(Poojari et al. 2008)
Conditional-Value-at-risk (CVAR)	(Poojari et al. 2008)
Visibility index -quantity of exchanged information -information quality in terms of accuracy -information freshness	(Caridi et al. 2010) (Gunasekaran et al. 2001)
Total distribution costs	(Caridi et al. 2010) (Gunasekaran et al. 2001) (Gunasekaran and Kobu 2007) (Brewer and Speh 2000)
Inventory holding cost (per unit, per square foot)	(Caridi et al. 2010) (Gunasekaran and Kobu 2007) (Chan and Qi 2003) (Brewer and Speh 2000)
Backorder penalty costs	(Caridi et al. 2010) (Gunasekaran and Kobu 2007)
Variance of profits	(Li and Zhao 2009)
Difference of variances of profits	(Li and Zhao 2009)
Cash-to-cash cycle time	(Manuj and Mentzer 2008) (Farris and Hutchison 2002) (Brewer and Speh 2000)
Logistics cost per unit	(Brewer and Speh 2000)
Organizational costs	(Neureuther and Kenyon 2009)
Probabilistic financial risk	(You et al. 2009)
Return on investment	(Min and Zhou 2002) (Gunasekaran et al. 2001) (Brewer and Speh 2000)
Return on supply chain assets (consumer profitability / average supply chain assets deployed during the period)	(Brewer and Speh 2000)
Percentage of supply chain target costs achieved	(Brewer and Speh 2000)
Inventory level	(Caridi et al. 2010) (Manuj and Mentzer 2008) (Kleijnen and Smits 2003)
Inventory productivity	(Chan and Qi 2003)
Working inventory rate (percentage of working inventory to total inventory held)	(Chan and Qi 2003)
Stock unit utilization (storage space utilization)	(Chan and Qi 2003)
Flow rate (ratio of inventory level to average inventory cycle time)	(Chan and Qi 2003)
Service level	(Caridi et al. 2010) (Gunasekaran et al. 2001)
Service level compared to competitors	(Gunasekaran et al. 2001)
Customer perception of service	(Gunasekaran et al. 2001) (Brewer and Speh 2000)
Fill rate (also confirmed fill rate)	(Caridi et al. 2010) (Kleijnen and Smits 2003) (Chan and Qi 2003) (Brewer and Speh 2000)
Lead time	(Manuj and Mentzer 2008) (Gunasekaran et al. 2001)

Metrics	Source
Order cycle time (time for order entry, planning, sourcing, assembly and follow up time, and delivery)	(Gunasekaran et al. 2001) (Brewer and Speh 2000)
cycle efficiency (total value-added / total time in supply chain)	(Brewer and Speh 2000)
Delivery performance	(Caridi et al. 2010)
Number of "perfect orders"	(Gunasekaran et al. 2001) (Brewer and Speh 2000)
Stock-outs (stockout rate)	(Manuj and Mentzer 2008) (Chan and Qi 2003)
Delays to customers	(Manuj and Mentzer 2008) (Kleijnen and Smits 2003)
Product availability	(Caridi et al. 2010)
Flexibility	(Caridi et al. 2010) (Qiang and Jingjuan 2010) (Gunasekaran et al. 2001)
Responsiveness	(Caridi et al. 2010)
Quality	(Caridi et al. 2010)
Structural reliability	(Neureuther and Kenyon 2009)
Consequence score	(Neureuther and Kenyon 2009)
Process efficiency	(Neureuther and Kenyon 2009) (Gunasekaran and Kobu 2007)
Risk index	(Neureuther and Kenyon 2009)
Risk factor (probability of occurrence of threat * consequence * value of asset)	(Pai et al. 2003)
Risk factor aggregate (combination of all risks)	(Yan et al. 2008)
Exposure (number of different types of risk events that occur in a given time period)	(Manuj and Mentzer 2008)
Coherent risk measure	(Ahmed et al. 2007)
Supply disruptions	(Manuj and Mentzer 2008)
Recovery capability	(Craighead et al. 2007)
Warning capability	(Craighead et al. 2007)
Downside risk	(You et al. 2009)
Upper partial mean	(You et al. 2009)
Risk premium (basis for a rational balance between expected value of investment performance and variance)	(You et al. 2009)
Resiliency	(Zongxue et al. 1998)
Vulnerability	(Zongxue et al. 1998)
Logistics index	(Hausman et al. 2005)
Premium freight usage	(Manuj and Mentzer 2008)
Asset utilization -net asset turns (ratio of total gross revenue to working capital) -inventory turns (ratio of annual costs of goods sold to average inventory investment) -cube utilization (ratio of space occupied to space available)	(Min and Zhou 2002) (Gunasekaran et al. 2001)

Metrics	Source
Supply chain density -average geographical spacing between nodes -number of dense areas within a supply chain	(Craighead et al. 2007)
Supply chain complexity (total number of nodes + total number of forward, backward, and within-tier materials flows)	(Craighead et al. 2007)
Node criticality	(Craighead et al. 2007)
Extent of co-operation	(Gunasekaran et al. 2001) (Brewer and Speh 2000)
Reliability	(Zongxue et al. 1998) (Gunasekaran and Kobu 2007) (Chan and Qi 2003)
Sales/inventory ratio	(Kleijnen and Smits 2003)
Part/material size	(Gunasekaran et al. 2001)
Range of product and services	(Gunasekaran et al. 2001) (Gunasekaran and Kobu 2007)
Number of choices offered relative to response time *	(Brewer and Speh 2000)
Percentage of goods in transit	(Gunasekaran et al. 2001)
Perceived value of product	(Gunasekaran and Kobu 2007)
Damage rates	(Brewer and Speh 2000)
Error rates	(Brewer and Speh 2000)
Number of customer contact points	(Brewer and Speh 2000)
Product finalization point (measure of postponement)	(Brewer and Speh 2000)
Product category commitment ratio**	(Brewer and Speh 2000)
Total value [(quality * service level) / (costs * lead time)]	(Mason-Jones et al. 2000)
Number of shared data sets relative to total data sets	(Brewer and Speh 2000)
Market performance	(Caridi et al. 2010)

*ratio that relates how effectively the supply chain is able to offer variety to its customers without unduly lengthening the time it takes to create this variety

**measures the extent to which supply chain partnerships truly exist, or assesses the potential risk to which each partner is exposed within a supply chain relationship) (numerator is percentage of the seller's total product category sales that are sold to a particular customer, denominator is percentage of that customer's product category needs that they bought from that seller

From Table 8, the metrics most applicable to the AF supply chain are: total distribution cost, inventory holding cost, percentage of supply chain target costs achieved, delays to customers, inventory level, inventory productivity, working inventory rate, lead time, part/material size, percentage of goods in transit, error rates, product category commitment ratio, and number of shared data sets relative to total data sets.

Metrics that are not directly applicable to the AF supply chain are those metrics dealing with profit.

2.5.3 *Air Force Specific Metrics.*

The primary goal of the Air Force is to support the warfighter while satisfying budgetary constraints. This is in contrast to the primary goal in industry of making profit. Because of this difference in goals, the Air Force uses some metrics that are not germane to industry. Mission Capability, Aircraft Availability, Total Non Mission Capable Supply (TNMCS) rate, Total Requirements Variance (TRV), and MICAP incidents and hours are a few of the AF specific metrics. Chapter 5 provides further explanation of these metrics.

2.5.4 *Summary.*

Supply chain literature provides a seemingly endless list of performance metrics and risk metrics, but the literature is geared toward consumable item supply chains. Although there is some overlap with consumable item supply chain metrics, our research provides risk metrics specific to reparable item supply chains.

3 Flexible Supply Chain Modeling and Analysis Framework: Integration of Software Agents with Agent Based Simulation and Risk Measurement

3.1 Overview

As stated by Fox et al. (2000) the next generation supply chain management system should be distributed, dynamic, intelligent, integrated, responsive, reactive, cooperative, interactive, anytime, complete, reconfigurable, general, adaptable, and backwards compatible. Work extended from Fox et al. (2000) focuses on mass customization along with message passing and task decomposition and dispersal. With the goal as stated by Fox et al. (2000), we developed a supply chain risk management framework that combines software agents, variable resolution agent based simulation, and a risk metrics component as depicted in Figure 2. Software agents collect, scrub and analyze data to provide input to the simulation. The agent based simulation models

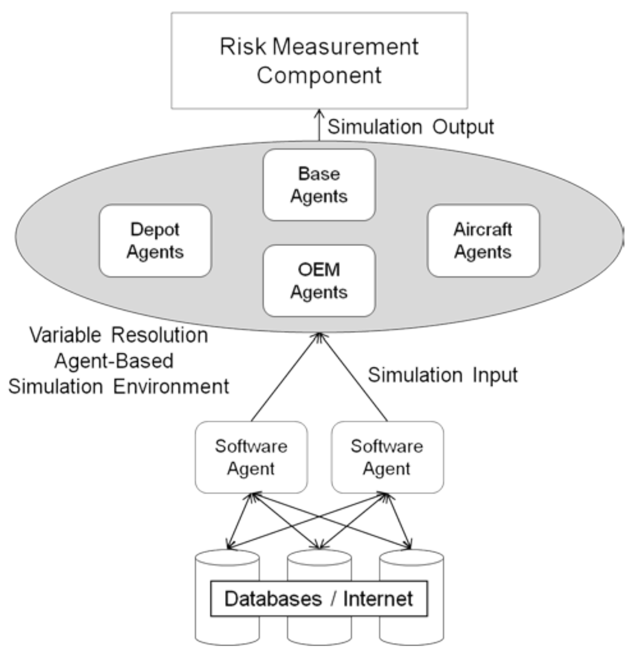


Figure 2 - Supply Chain Modeling and Analysis Framework

selected portions of the AF supply chain for different disruption scenarios and other potentially risky situations. Simulation output is then used to calculate supply chain performance and risk metrics.

This framework can be used to recurrently assess risk and supply chain performance or can be used to assess risk mitigation strategies. Software agents can periodically (daily, weekly, etc.) collect and analyze data, then execute simulation runs, and finally display current (and past) performance and risk metrics. This technique could provide information about a risk event occurring instantaneously or events leading up to a supply chain problem. To determine what actions to take after supply chain disruptions occur, the framework could be used to analyze effectiveness of several risk mitigation strategies.

This chapter outlines our supply chain modeling framework and provides details on integrating software agents and agent based modeling and simulation (ABMS). It also introduces our risk measurement component which is discussed in more detail in Chapter 5.

3.1.1 ***Framework Development.***

Our framework provides a flexible design to model and analyze a selected portion of a supply chain, tying together a number of specially designed tools, as shown in Figure 2. The Supply Chain Optimization through Risk and Predictive Analytics for Decision Support (SCORPAD) model, developed by EDAptive Computing, Inc. in support of the Air Force Global Logistics Support Center (AFGLSC), provides some similar capabilities using a discrete event simulation directly linked to Air Force databases (AFGLSC 2011).

Our framework expands input data flexibility and capability by utilization of software agents to intelligently pull and pre-process data before tying into an agent based simulation. Such an agent based approach is seeing increased use for supply chain modeling in the literature and provides a more natural fit for supply chain components and interactions. An added feature of our agent based simulation environment is incorporation of a variable resolution logic structure. Output from our simulation then feeds into our risk measurement component with newly developed metrics applicable to reparable parts. The following sections provide more detail on the three major components of our framework.

3.1.2 ***Software Agents for Data Mining Simulation Input.***

Our research uses software agents for data mining because raw data is often incomplete, contains outliers, and constantly changes. Thus, software agents can automate data mining and scrubbing to reduce time and resources needed to constantly analyze this data. Cougaar (Cognitive Agent Architecture) is a software agent architecture developed under the Advanced Logistics Project (ALP), a joint Defense Advanced Research Projects Agency (DARPA) / Defense Logistics Agency (DLA) research project to investigate, develop, and demonstrate technologies that will make a fundamental improvement in logistics planning and execution efficiencies. Extensions added to Cougaar, under the DARPA follow-on program UltraLog, provided the ability to build and maintain realistic high fidelity logistics plans under stress, and dynamically replan as required to cope with changes in the requirements, environment or availability of resources (Carrico and Greaves 2008). We propose using the Cougaar architecture

because it has existing application in military logistics. Similar to Srinivas and Harding (2008) agents may include: data collection agents that are responsible for defining the data needs and data acquisition; data cleaning and pre-processing agents; and mining agents. Data needed for the simulation include inventory levels (depot, base, etc.), repair time (depot, base, etc.), and network connections (i.e. suppliers, customers). Further details on integrating software agents and ABMS are provided in Section 3.2.

3.1.3 ***Agent Based Simulation.***

We use agent based simulation to model the Air Force supply chain because of its natural fit with supply chain entities (e.g. depot, base, aircraft, etc.). To provide a natural link with the Java based software agents, we selected a Java agent based simulation platform, AnyLogic. AnyLogic was rated top in a trade study on agent based simulation software conducted by Nikolai and Madey (2009). In addition, AnyLogic has become an industry leader with customers such as Caterpillar, Boeing, IBM, McDonald’s, National Aeronautics and Space Administration (NASA), Air Force Research Laboratory, US Air Force Air Mobility Command, and the US Navy. Another advantage of AnyLogic is the ability to generate a Java applet that allows users to run a model anywhere. Therefore, the proposed framework could be developed such that users will not need to purchase an AnyLogic runtime license.

An example of our agent based simulation supply chain logic can be found in an independent study conducted by the author (Harper 2010). This work extended research by Krishnamurthy et al. (2008) and used Netlogo software to simulate a generic AF

supply chain, as depicted in Figure 3. Agents included original equipment manufacturers, depots, bases, aircraft, parts, and orders.

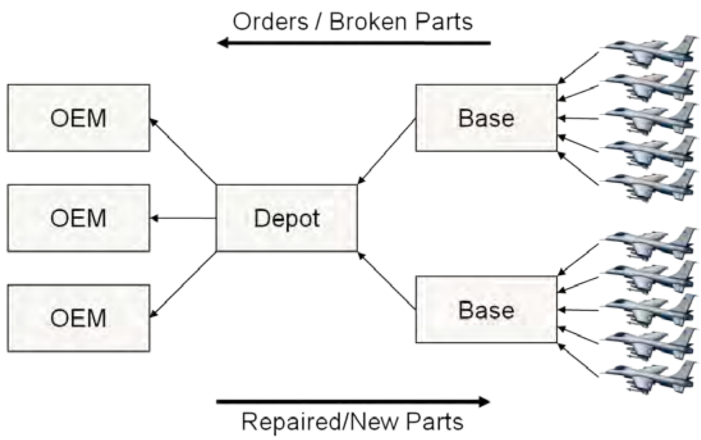


Figure 3 - Aircraft Supply Chain Flow

Part of our expanded agent based simulation environment includes guidelines and logic to define agents and interactions in such a way as to allow for easy substitution of agents with differing levels of fidelity based upon the needs of a particular simulation study. We incorporate variable resolution by combining hierarchical design with data driven modeling. More details on our implementation are discussed in Chapter 4.

3.1.4 *Supply Chain Performance and Risk Metrics Framework.*

The proposed metrics framework we discuss in Chapter 5 is designed specifically for reparable item supply chains. The metrics include existing metrics such as working inventory rate, stock unit utilization, flow rate, and product finalization point. The product finalization point provides a measure of postponement that will be helpful for repair kits. New metrics include time average number of backorders, the ratio of a parts' inventory cost to its size and average time a part spends on shelf, which is a variation of the cash-to-cash metric. The correlation between the metrics should be considered, so

certain aspects or problems are not over-emphasized by using several metrics depicting the same thing. Other considerations to be taken into account are lag analysis and predictability of the metrics (forecasting).

Following suggestions by Globerson (1985), the developed metrics framework is: based on AF objectives; comparable to other performance criteria used by similar organizations; clearly defined in purpose; ratio-based rather than absolute number; determined through discussions with the parties involved; and objective. Other suggestions, by Maskell (1989) that were considered in developing the metrics framework were: nonfinancial measures should be adopted; measures should vary between locations (departments or companies); measures should be simple and easy to use; and measures should stimulate continuous improvement.

3.2 Integrating SA’s and ABMS

Literature on software agents depicts the usefulness of software agents in decision support tools, and specifically data mining. Although there are several agent design issues that must be considered, software agents provide a great mechanism for data mining databases for useful information to aid supply chain risk management. However, literature on software agent decision support tools does not depict a natural and easily implemented modeling technique necessary for analyzing large supply chains. Thus, our research fills this gap by integrating data mining software agents with agent based modeling and simulation (ABMS) agents. Software agents in context to our framework are independent computer programs that operate outside a software platform and perform

in real time. Simulation agents only operate within a simulation software platform and perform in simulated time.

Software agents in theory can collect, scrub, analyze and output data. Analysis could include fitting multiple distributions, analyzing distributions for best fit, and fitting aggregation models for variable levels of resolution. Selecting the best distribution for data is considered something of an art, so relying solely on code to fit and test distributions might not be a favored option. In that case, fitting of distributions can be performed manually in a preprocessing stage, such that the software agents only need to collect data and calculate the distribution parameters. Another option is to add person-in-the-loop capability to the software agents, such that several distributions are automatically fit, but the user makes the final selection based on fitness measures and theory. This logic is similar for selecting aggregation models. For example, should process times of smaller parts be simply averaged for the aggregate process times of the larger assembly, or should meta-models be used for aggregation.

Software agents can be coded to draw random samples or more complex algorithms can be employed to collect the desired data. Some initial issues to consider with random samples are how much data to collect and how well does the data represent the actual process. Depending on how the data is listed in the database and the data collection technique, there could be correlation issues with the collected data points. Another problem that could arise is bad/dirty data. Since most raw data contains outliers and bad data, software agents should be designed such that these complications are handled. When software agents are coded to select the best distribution there could be concern that the distribution will change from run to run. That is, the framework this

week could specify different distributions than the previous week. In contrast, when manual preprocessing is performed, it is assumed that the predetermined distribution remains valid throughout use of the framework. To ensure the distributions are valid representations of the data, it is necessary to perform preprocessing every time the framework is utilized.

Most ABMS platforms contain pre-coded logic and functions, such as event handling and message passing, which reduce model development time. Other helpful capabilities include charts and tables that collect output from the simulation, which can be exported in several formats for ease of analysis. Developing a supply chain decision support model based on an agent based model incorporating software data mining agents requires extensive coding and linking with data structures to achieve the capabilities of an integrated software platform. Our approach combines the capabilities of these components into a well designed modeling and analysis framework. Our framework also considers variable resolution, which structures models such that different levels of insight can be gained from a single model. By combining the advantages of software agents with the advantages of simulation agents, our framework provides a powerful, flexible framework for analyzing complex supply chains.

3.3 Application

Our modeling and analysis framework is applied to a landing gear portion of the F-16 reparable item supply chain. Simulation agents include parts, aircraft, bases, depots, and original equipment manufacturers, as depicted in Figure 3. Mission capability and

other performance measurements are assessed for different inventory policies throughout the supply chain. Chapter 6 contains a more detailed discussion of this application.

Software agents are not used on the actual AF databases for our research, so surrogate databases were developed. These surrogates use similar database software and have similar structure to the actual AF databases, but reside on a local computer. While the use of software agents is demonstrated on a smaller network, the concept is scalable to a larger network with the primary constraints being bandwidth and firewall security. The former is remedied by increased capacity, if necessary, while the latter is remedied by reconfiguration of the firewalls to handle software agents. This aspect is beyond the current scope of our research. We specifically use software agents to collect a random sample of raw data from an Access database. The software agents calculate parameters specific to a distribution that has been determined in a preprocessing phase. For example, assume that an exponential distribution fit well, thus the software agents collect a random sample and calculate the mean for the exponential. Parameter values are then stored in another database that is linked to the ABM in AnyLogic software.

3.4 Summary

This chapter provides an overview of our primary research contribution, a well defined supply chain modeling and analysis framework that integrates software agents, variable resolution agent based modeling and simulation, and a reparable item risk metrics component. Furthermore, this chapter describes the integration of software agents and ABMS agents, a subsequent research contribution.

4 Agent Based Simulation Design for Aggregation and Disaggregation

4.1 Overview

Traditionally, simulation models were used to analyze a specific problem, so model development was rather straight forward and did not require variable levels of detail. With higher complexity systems of today, a single model is often used to analyze a wider spread of problems. Thus, models must have varying levels of fidelity in order to answer the different questions associated with these highly complex systems. Low resolution models are used for initial investigations, comprehension, systems analysis and policy analysis, decision support, adaptability, low cost and rapid analysis, and making use of low-resolution knowledge and data (Davis and Hillestad 1993). High resolution models are used in understanding phenomena, representing knowledge, simulating reality, calibrating or informing lower-resolution models, and making use of high-resolution knowledge and data (Davis and Hillestad 1993).

The concept of using a single model with variable levels of detail, is not new to discrete event simulation (e.g. Davis and Hillestad 1993), but little research exists with a focus on agent based simulation. This paper lays out the process and considerations that go into developing variable fidelity agent based simulation models. To do this, it is necessary to define terms found in this area of literature. Specifically, we will define and describe the relationship between resolution, scalability, flexibility, and aggregation.

When modeling, resolution can refer to entities, attributes, logical dependency, processes, spatial orientation, or temporal orientation. Table 6 provides military examples

of how these six aspects of a model may change with levels of resolution. Granularity, levels of description, and levels of detail are used synonymously for resolution.

Scalability is defined by Rana and Stout (2000) as “the ability of a solution to a problem to work when the size of the problem increases.” Although problem size includes dimensions, such as the data (rules) the agents are operating on (with) and diversity of agents, literature focuses on the number of entities involved.

Flexibility of a simulation refers to it being generic enough to allow for modeling of similar systems by altering the input data used to execute the model (Brown 2010). This concept of using a model for similar systems is referred to as model “re-use” and altering input data for modeling similar systems is known as data-driven modeling.

As defined by the Department of Defense Modeling and Simulation Master Plan (Department of Defense 1995), aggregation is “the ability to group entities while preserving the collective effects of entity behavior and interaction while grouped.” Axtell (1992) defines model aggregation as the decrease in the dimensionality of a simulation model through the fusion of model variables into composite variables. Operators, such as sum, average, minimum, and maximum are the most common form of data and information transformation into an aggregation model (Rodriguez 2008). Aggregation has an inverse relation to resolution. So, as resolution decreases the level of aggregation increases by combining agents and replacing detailed processes with approximations.

Figure 4 depicts the relationship between the various terminologies with respect to an aircraft supply chain model. Throughout this paper we will use model resolution when describing levels of model fidelity. To illustrate, an example of a high resolution model with no aggregation is modeling details of individual system performance (such as

aircraft), while an example of low resolution model with high aggregation is modeling a large theatre level conflict.

Section 4.2 presents the standard procedure designing and implementing agent based modeling and simulation (ABMS). Section 4.3 lays out the mathematical theory of variable resolution ABM. Section 4.4 proposes guidelines for planning and designing agent structure for handling variable levels of resolution. The proposed guidelines are then demonstrated by a simple example in Section 4.5, followed by concluding remarks in Section 4.6.

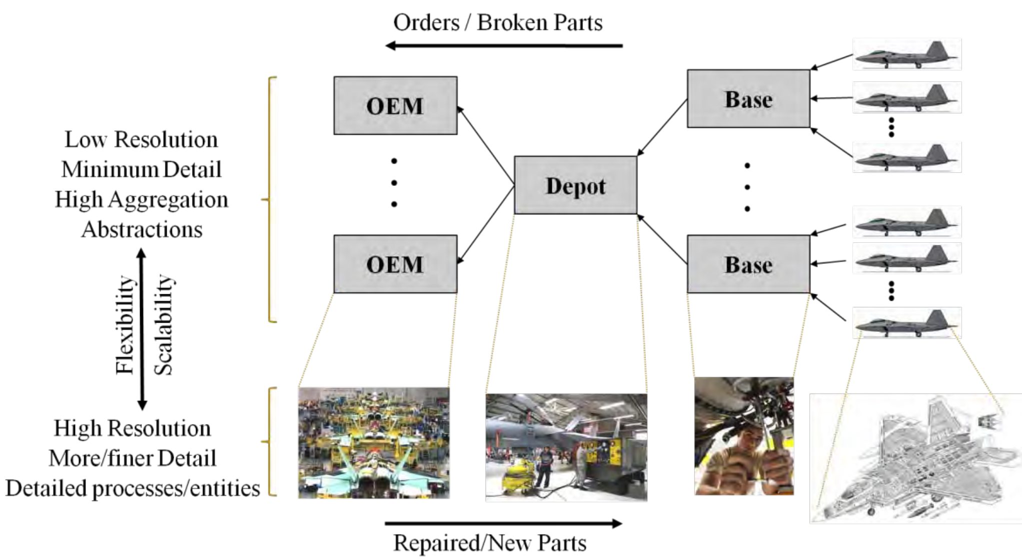


Figure 4 - Range of Model Fidelity (Axe 2010, Lockheed Martin 2011, Globalsecurity.org 2011, PACAF 2011, WPAFB 2011)

4.2 Standard ABMS Design Methodology

As with any simulation study, the first design step is to identify the purpose of the model, the questions the model is intended to answer and the potential users (Macal and North 2005). Then, systematically analyze the system under study, identifying components and component interactions, relevant data sources, and so on (Macal and

North 2005). With a basic understanding of the objectives and system under study, the general steps in building an agent based simulation are depicted by Macal and North (2006) as follows:

1. Agents: Identify the agent types and other objects (classes) along with their attributes
2. Environment: Define the environment the agents will live in and interact with
3. Agent Methods: Specify the methods by which agent attributes are updated in response to either agent-to-agent interactions or agent interactions with the environment
4. Agent Interactions: Add the methods that control which agents interact, when they interact, and how they interact during the simulation
5. Implementation: Implement the agent model in computational software

Normally there is a constant interplay between steps in building an agent based simulation. Once the development phase is complete the analysis phase is executed, which is typical for general simulation studies. The standard procedure for building and implementing agent based simulation models is depicted in Figure 5.

Current ABMS procedure fails to accommodate variable resolution models in the initial planning, agent and agent rule design, data collection and entry, and model execution steps. While identifying the purpose of the model and the questions the model is intended to answer, there must be some delineation between the different levels or resolution needed for these questions. This is not a trivial process, but can be eased by systematically analyzing the system under study and determining what data is available.

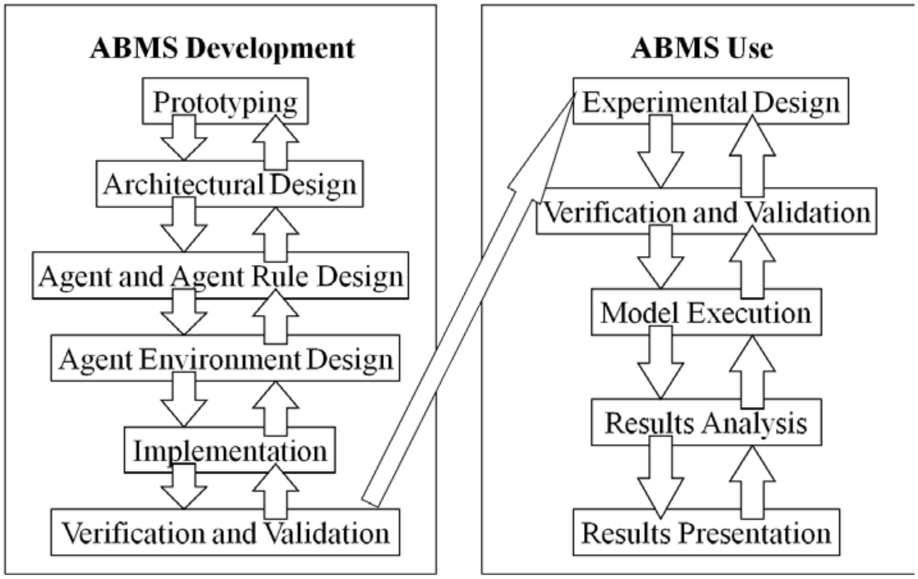


Figure 5 - Standard ABMS Procedure (North and Macal 2007b)

As described in Section 4.4, the way agents are designed will affect the ease of switching levels of resolution. Since multiple levels of resolution have different data requirements, the data collection and entry process is a key step in ABMS for aggregation and disaggregation. More data analysis is necessary to validate the method of data aggregation, so data collection and data analysis will generally take more time than standard ABMS. However, this is balanced by the ability to model and analyze selected parts of the system at a high level of detail or more of the system at an aggregated level. Finally, the model execution process requires some data input changes to change levels of resolution.

4.3 Math Framework for Variable Resolution ABMS

This section discusses a mathematical framework developed to describe the logical structure of a discrete event simulation. We then explain modifications to this

framework for our variable resolution ABMS approach, highlighting where aggregation of input data and agents fits in.

4.3.1 ***Discrete Event Simulation.***

Leemis (2004) presents a framework for discrete event simulation, as provided in Figure 6 along with the subsequent description of the sets and transformations shown.

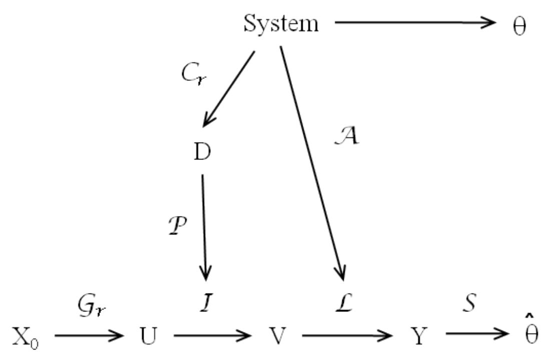


Figure 6 - Math Formulation for Discrete Event Simulation (Leemis 2004)

> The upper-case letters X_0, U, V, Y, $\hat{\theta}$, θ, and D denote ordered sets containing one or more numbers. To avoid writing "one or more numbers" in our descriptions of these sets, we assume that there are multiple numbers in the sets. The description of these ordered sets follows.
>
> - X_0 is a set of seeds for a random number generator, one for each stream used in the implementation of the discrete event simulation model.
> - U is a set of random numbers created by using the random number generator $\mathcal{G}r$ to transform the seeds in the set X_0 to random numbers.
> - V is a set of input data ("variates") created by applying the input model $\mathcal{I}$ to the set of random numbers U.
> - Y is a set of output data generated by applying the logic model $\mathcal{L}$ to the set of input data V.
> - $\hat{\theta}$ is a set of point estimators for the unknown system measures of performance θ, calculated as a function of the output data Y.
> - θ is the corresponding set of measures of performance associated with the system of interest.

- D is a set of system data values collected on appropriate elements of the system of interest in order to build an input model $\mathcal{I}$.

The calligraphic letters $\mathcal{G}r$, $\mathcal{I}$, $\mathcal{L}$, $\mathcal{S}$, $\mathcal{C}r$, $\mathcal{P}$, and $\mathcal{A}$ are all associated with arrows. These letters denote transformations, probability models, data collection methods, assumptions, etc., as described below.

- $\mathcal{G}r$ is a random number generator used to transform the seeds in the set X_0 to random numbers in the set U.
- $\mathcal{I}$ is the input model used to transform the set of random numbers U to the set of input data V. The process of transforming U to V is known as random variate generation.
- $\mathcal{L}$ is the logic model that captures assumptions made about the system into transformations (often formulated as algorithms) that are used to transform the set of input data V to the set of output data Y.
- $\mathcal{S}$ is a statistical estimation procedure. The S connecting the set of output data Y and the set of point estimates of the measures of performance $\hat{\theta}$ involves computing statistics, which are functions of the set of output data Y (e.g. sample mean, sample median, or sample variance).
- $\mathcal{C}r$ denotes the data collection procedures from the system of interest.
- $\mathcal{P}$ involves the process of formulating a probabilistic input model that adequately describes the set of data collected in D. The *P* connecting the set of system data values D and the input model $\mathcal{I}$ involves either resampling or fitting a parametric model to the data set.
- $\mathcal{A}$ denotes assumptions made on the system of interest. These assumptions are used to create the logic model $\mathcal{L}$ describing the operation of the system. (Leemis, 37-38, 2004)

4.3.2 ***Agent Based Modeling and Simulation.***

The discrete event framework provided by Leemis (2004) is adapted, as depicted in Figure 7, for variable resolution ABMS. Differences between the discrete event formulation and ABMS formulation primarily fall under the input model, which now also

captures some of the structural assumptions about the system of interest. For discrete event simulation, input modeling captures the process parameters, while input modeling for ABMS captures agent behavior/decision logic and agent interactions. Furthermore, variable resolution ABMS input modeling builds on agent hierarchy for defining aggregation models. Our variable resolution ABMS framework also incorporates use of software agents for data collection procedures and the scalability of performance metrics based on the resolution of agent input models. The description of the adapted sets and transformations follows.

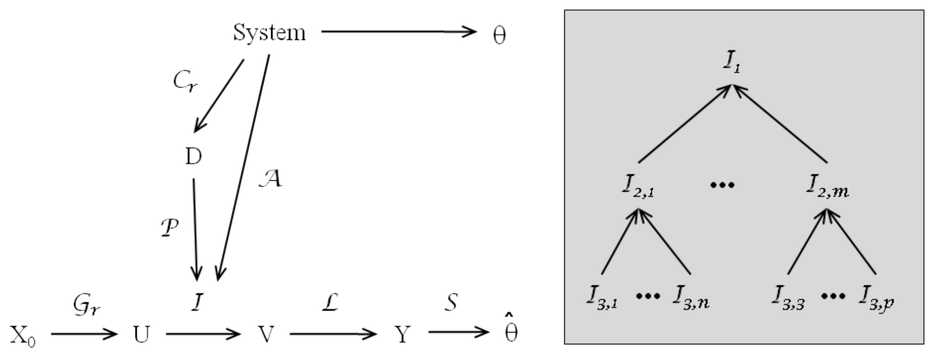


Figure 7 - A Framework for Variable Resolution ABMS

- $\mathcal{I}$ represents the input model consisting of a well defined hierarchy of agent classes as depicted on the right hand side of Figure 7. These agents represent both active players in the system as well as the environment. The top level, $\mathcal{I}_1$, represents the input model for all agents at the most aggregated level. Each subsequent level represents a modified agent or agents for a higher level agent class, with the modified agents containing more detailed data and methods to provide a higher fidelity representation of selected agents for the study at hand. With a supply chain perspective, player agents include retailers, wholesalers,

distribution centers, customers, and suppliers. Environment agents define the conditions that influence how player agents interact. These environment agents may represent competition, transportation, and the economy as well as disruptive influences such as terrorists or natural disasters. Agents are comprised of decision logic, process data, and agent interactions. The data collection procedures and the probabilistic modeling feeding into the input model may both be performed at least in part by software agents.

- $\mathcal{Cr}$ denotes the data collection procedures from the system of interest. For our framework this process involves use of software agents gathering data to store in set D or to process in forming a probabilistic input model.
- $\mathcal{P}$ involves the process of formulating a probabilistic input model that adequately describes the set of data collected in D. This process involves fitting models to data capturing agent behaviors and may be performed by software agents, with the option of including the user in the loop, or performed purely by the user in a preprocessing step. Models developed are based on the level of fidelity required and include the formulation of aggregation models.
- $\mathcal{A}$ denotes assumptions made on the system of interest. Note the shift of these assumptions to the input model to account for the formulation of agent rules for behavior and decision logic.
- $\mathcal{L}$ is the dynamic implementation of the agents, including the input models, agent behaviors and agent interactions. Essentially this is the process of running the

simulation and allowing the agents to interact with each other and their environment.

- S is a statistical estimation procedure with scalable performance metrics based on the resolution of agent input models.

4.4 Planning and Designing Agents for Variable Resolution

Generic challenges in variable resolution modeling, as discussed by Davis (1993), include:

- getting the concepts and names straight
- completing sets of variables and functions (i.e. defining the reference model)
- drawing relationships and mappings
- deciding the form of reasonable aggregate equations relative to detailed equations (requires theoretical analysis)
- finding conditions under which aggregation equations might be reasonably valid (requires theoretical analysis)
- expressing aggregate-model parameters in terms of outputs of detailed model (requires theoretical analysis)
- deciding on cases (e.g. scenarios) to be distinguished and how to make calibrations for each case—e.g., how to determine weighting factors over case and time so that calibrations will be appropriate for context of larger applications (requires theoretical analysis)

Techniques and recommendations to overcome these challenges are provided in Davis (1993). Furthermore, practices from object oriented design can help overcome the

challenges. For example, a key step in ABMS is defining agent interactions and behavioral logic. This decision logic structure is easier to capture with respect to agents than drawing relationships and mappings in discrete event simulation.

The two primary issues with changing levels of resolution in an agent based model are the agents and the processes. At different levels of resolution what agents are active and with what agents do they interact? What processes must be performed on the agents? These are some of the questions that must be asked when planning and designing agents for variable resolution agent based models.

The basis of the proposed methodology is the combination of hierarchical design with data driven modeling. This method is similar to IHVR by (Davis and Hillestad 1993), but adapted for agent based modeling. As with IHVR, the proposed methodology utilizes lookup tables and different levels of abstraction for processes, but also for the agents themselves.

4.4.1 ***Planning Phase.***

The planning phase is the most important phase when developing agent based models with variable resolution. In this phase it is still necessary to identify the purpose of the model, the questions the model is intended to answer and the potential users. However, for variable resolution it is also necessary to delineate between the different levels of resolution needed for the questions to be answered. Specifying the levels of resolution affects what agents are needed and what behaviors and interactions are appropriate. Incorrectly defining the levels of resolution can invalidate and increase difficulty in data collection and building of the agent based model.

Systematically analyzing the system under study and determining what data is available will aid the process of defining the levels of resolution. Most often availability of data is the key driver in variable resolution modeling. Tools such as process mapping and cause and effect diagrams, along with theory (e.g. queuing theory) can also help with determining which details to suppress and which to expand.

Along with planning the agents, agent behavior, interactions and processes, simulation input and output must be considered in the initial planning phase. Inputs must be collected to accommodate all levels of resolution and the appropriate aggregation models. A simple method for eliminating the need to change model logic to handle output at different resolutions is to report all outputs. In context for an aircraft supply chain, assume aircraft are comprised of engine, landing gear, and body agents. Design the model to collect time to repair data for each agent type (aircraft, engine, landing gear, and body agents). A high resolution model might model failures at the component level (e.g. engine or landing gear) and a low resolution model might aggregate the components into failure of the aircraft. With the high resolution model there will be output data for all agents, while with the low level there will only be output data for aircraft agents. By including all output data you do not have to change the code for levels of resolution.

4.4.2 ***Hierarchically Designing Agents.***

As highlighted by Davis and Hillestad (1993) object-oriented methods can help greatly in developing variable resolution in entities, attributes, and logical-dependency. A key benefit of object-oriented modeling is modularity, which encourages hierarchical representation of objects and attributes (Davis and Hillestad 1993). With object-oriented

modeling subclasses inherit attributes (fields) and processes (methods) from higher classes. Many agent based simulation packages enable hierarchy of objects and processes.

With variable resolution ABMS, different agents, agent behavior, resources, and processes may be necessary. To accommodate this, agents should be defined hierarchically and agent behavior logic should be designed similar to the hierarchical processes depicted in section six of (Davis 1993). With hierarchical behavior logic, switches and gates can be employed within the hierarchy to activate the appropriate behavior logic for the corresponding level of resolution. Without designing agents and agent logic hierarchically it would be necessary to manually change large portions of the model to change levels of resolution. For details of how to do hierarchical design with cross-talk between branches and cycling refer to Davis and Huber (1992).

A military example where hierarchy of object-oriented methods would be beneficial is the scenario where a platoon comprised of separate entities encounters an enemy battalion that is modeled as a single entity (Davis and Hillestad 1993). For this scenario the battalion could be disaggregated into separate entities or the platoon's entities could be aggregated into a single entity. With respect to a supply chain, an example is modeling depot agents at a low level of resolution and modeling bays, equipment, and personnel agents of a depot at a high level of resolution.

4.4.3 ***Designing Agent Interactions.***

A key problem with variable resolution in ABMS is changing interactions between agents. Hard coding messages between agents could require extensive effort and

model changes to switch between various levels of resolution. For a low resolution aircraft supply chain model, broken parts may simply be sent to a base for repair whereas the higher resolution model may send broken parts to the flightline or backshops at the base. Thus, there is a difference in sending broken parts to the aggregate agent, the base, versus sending broken parts to the detailed flightline or backshop. How should agents be designed such that interactions between agents can easily be changed?

Instead of hard coding interactions between agents, lookup tables can be used. With object oriented modeling and systems that do not have individualized interactions the necessary lookup tables are straightforward and changing the tables for different resolutions would not be time consuming. Assume at low resolution all broken parts are sent to base agents for repair, but sent to flightlines and backshops at a higher resolution. Then the lookup table for the lower resolution would simply specify to send the message to repair the part to its home base, which is an attribute of the agent. Changing to the higher resolution model would only require specifying to send the message to repair the part to its home flightline or backshop. A percentage or condition can also be depicted via table to determine where, flightline or backshop, the message should be sent.

The technique of lookup tables for agent interactions becomes cumbersome when agents of the same type must interact with specific agents of another type. For example, part A can only be repaired at the flightline and part B can only be repaired at the backshop. In this scenario the size of the lookup table would grow rapidly with the number of part types and repair locations. With this type of model use of gates and switches in the hard code might be easier. This would enable changing a single variable that links to different switches in the model to accommodate the desired resolution.

If agents and processes are strictly hierarchical, then agent interactions can be inherited from higher classes. That is, if agents in a subclass follow similar processes and interactions as agents in the parent class, then the messages can be inherited from the parent class. In the aircraft supply chain example, assume an aircraft gearbox contains a pump, a gear assembly, and a circuit board. If the gearbox is repaired at a home base and the pump, gear assembly, and circuit board are also repaired at the home base, then a lookup table is not necessary. The message to send the broken part agents to the home base can be inherited as a method from the gearbox agent.

4.4.4 ***Designing for Aggregate Process Data.***

Current literature provides numerous aggregation models for processes. Sum, average, minimum, maximum, and mode are some common aggregation models (Rodriguez 2008). Others include regression and distribution fitting to high resolution model output. These aggregation models can also be used in defining agent behavior.

When aggregating higher resolution processes, theory should first be used to abstract the process. For example, queuing theory. If no theoretical equations are available, then a common aggregation model that could be used is a weighted average of the best, worst, and most likely scenarios. Other common aggregation models, like minimum or maximum, may fit better at this level of aggregation. A final technique of process aggregation is running higher resolution models and fitting regression models and distributions to the resulting simulation output. The drawback of this method is a simulation model must already be operational, so model alterations to the existing model might be required to accommodate variable resolution.

Lookup tables are again recommended for implementing the aggregation models in the agent based model. For a supply chain example, break rates and repair times for individual parts would be specified in the lookup table with higher assemblies having no break rates or repair times. For a lower resolution model the lookup table would have no break rates or repair times for individual parts, but would specify aggregate parameters for the higher assemblies. Lookup tables could be used to specify distributions as well as parameter values. For example, if the process varies over time, then the lookup table would specify what distribution or regression model to be used for the corresponding level of resolution during the specified time period. A similar technique for specifying the distribution or aggregation model is implementation of gates or switches. For different levels of resolution gates/switches can be activated to run the correct aggregation model that would then utilize the lookup table values.

By planning and designing agents to reference lookup tables, the drawback mentioned previously is eliminated. That is, data for lower resolution models can successively be determined by running the higher resolution models and fitting an aggregate model to the simulation output. Since the agents were designed to reference lookup tables, there is no need to change the existing model.

As with any simulation, the aggregation models and the entire agent based simulation model must be verified and validated. Standard verification and validation (V&V) methods, such as comparison to historical data and expert assessment, are appropriate at specific levels of resolution in agent based simulation models. However, variable resolution along with object oriented design introduces complexities and

challenges for V&V. For detail on these complexities, challenges and techniques for V&V in the presence of these issues, refer to Balci (1997).

To automate the process of switching between levels of resolution during model execution and analysis phases, lookup tables can be linked to interface controls, such as a slider bar. For example, a slider bar can be coded to specify what agents to implement and change lookup table values according to the specified level of resolution.

A final recommendation for designing agent behavior and process logic is to consider the spatial and temporal orientation. When using decision logic, all time scenarios and spatial orientation must be accommodated. For example, at one level of resolution the model might run in days and all events occur in full days, while a different resolution model might run in hours. If decision logic for the first resolution level uses an equivalence condition alone (e.g. break time = current time, then part breaks), then switching to the resolution with hours will not work correctly because partial days are not considered in the decision logic. To accommodate hours, the logic should implement greater than (less than) along with the equivalence condition (e.g. break time >= current time, then part breaks). Without the greater than (less than) condition the break event will never trigger. For agents running at different time and spatial orientations refer to Pawlaszczyk and Strassburger (2009) and Chaturvedi et al. (2004).

4.5 Example

To demonstrate the proposed methodology a small theoretical aircraft supply chain model, as depicted in Figure 8, is used for analyzing different repair policies. Assume aircraft landing gear is comprised of two parts, A and B, each with a break rate and repair

rate. When a part breaks it is either repaired at the Base or sent upstream to the Depot for repair.

Assume the questions of interest are 1) How is aircraft availability affected by increasing the number of parts repaired at the base level? and 2) How is aircraft availability affected by increasing the number of landing gear assemblies repaired at the base level?

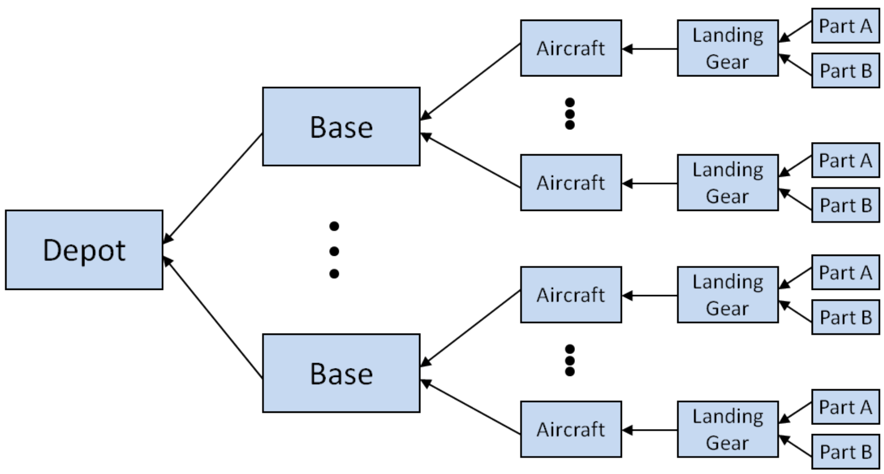


Figure 8 - Aircraft Supply Chain Example

The first question requires a high level of detail, where the active agents include Parts, Bases, and Depots. Since Landing Gear and Aircraft agents are used simply to track availability output there is no process data for these agents, as depicted in Table 9.

Table 9 - Process Parameters for High Resolution Model

Agent	Break Rate	Repair Rate at Base	Repair Rate at Depot	Shipment Time to Depot
Part A	15 days	2 days	1 day	2 days
Part B	25 days	5 days	2 days	2 days
Landing Gear	--	--	--	--
Aircraft	--	--	--	--

For the second question the Parts agents are aggregated to become the Landing Gear agents. Thus the lower resolution model for the second question includes Landing Gear agents, Bases and Depots. Table 10 shows the process parameters for the active

agents for this level of resolution. In this simple example the parameters for the Parts agents were averaged to find the process parameters for the Landing Gear.

Table 10 - Process Parameters for Low Resolution Model

Agent	Break Rate	Repair Rate at Base	Repair Rate at Depot	Shipment Time To Depot
Part A	--	--	--	--
Part B	--	--	--	--
Landing Gear	20 days	3.5 days	1.5 days	2 days
Aircraft	--	--	--	--

With hierarchical design and object-oriented programming, Aircraft agents form the super class, with successive subclasses Landing Gear agents, then Parts agents. Aircraft agents have six fields, or attributes, that correspond to the data specified in the process parameter tables. Figure 9 provides pseudo code for defining these agents hierarchically with object-oriented programming.

To demonstrate the use of lookup tables for agent interactions, the same aircraft supply chain example is used to answer questions regarding repair processes at the Base level. Assume the questions of interest are now 1) How is aircraft availability affected by repairing more parts on the flightline versus repairing parts in the backshops? and 2) How is aircraft availability affected by increasing the number of parts repaired at the Base?

Table 11 shows the agent interactions for repairing the Part agents at the Flightline and Backshop level, which is the higher resolution model. For the lower resolution model in the second question, Part agents interact with the Base agents, as depicted in the Table 12.

```
Class Aircraft {
 //Aircraft agents have 6 fields
 Home Base //Base to be repaired at
 Home Depot //Depot to be repaired at
 Break Rate = Aircraft Break Rate
 Base Repair Rate = Aircraft Repair Rate at Base
 Depot Repair Rate = Aircraft Repair Rate at Depot
 Shipment Time to Depot = Aircraft Shipment Time to Depot
 //Aircraft agents have 2 Methods
 Break {
        Time of Break = Current Time
        Send message to Home Base for Repair
 }
 Repaired {
        Time to Repair = Current Time – Time of Break //tracks the time to repair
        Time Operational = Total Simulation Time – Time to Repair for each break
        Availability = Total Simulation time / Time operational
 }
}
Class Landing Gear extends Aircraft {
 //Landing Gear a subclass of Aircraft - inherits the 6 fields, 2 methods from Aircraft
 //The process data is overridden for Landing Gear agents
 Break Rate = Landing Gear Break Rate
 Base Repair Rate = Landing Gear Repair Rate at Base
 Depot Repair Rate = Landing Gear Repair Rate at Depot
 Shipment Time to Depot = Landing Gear Shipment Time to Depot
}
Class Parts extends Landing Gear {
 //Part a subclass of Landing Gear - inherits the 6 fields, 2 methods from Landing Gear
 //The process data is overridden for Part agents
 Break Rate = Part Break Rate
 Base Repair Rate = Part Repair Rate at Base
 Depot Repair Rate = Part Repair Rate at Depot
 Shipment Time to Depot = Part Shipment Time to Depot
}
```

Figure 9 - Aircraft Supply Chain Example Agent Structure

Table 11 - Agent Interactions for High Resolution Model

Agent	Repair Message Sent To	Repaired Message Sent To
Parts (A, B)	Flightline / Backshop	--
Landing Gear	--	--
Aircraft	--	--
Base	--	--
Flightline	--	Parts (A, B)
Backshop	--	Parts (A, B)
Depot	EOM	Flightline / Backshop

Table 12 - Agent Interactions for Low Resolution Model

Agent	Repair Message Sent To	Repaired Message Sent To
Parts (A, B)	Base	--
Landing Gear	--	--
Aircraft	--	--
Base	Depot	Parts (A, B)
Flightline	--	--
Backshop	--	--
Depot	EOM	Base

As mentioned previously, in the simple case where all parts have the same logic, gates and switches can be used instead of lookup tables.

4.6 Summary

By combining hierarchical modeling with data-driven modeling the proposed methodology has extended the variable resolution modeling work to agent based modeling and simulation (ABMS). Existing literature explains variable resolution modeling for discrete event simulation, but variable resolution has never been extended to agent based modeling and simulation (ABMS). This work ties together a general framework for using ABMS for supply chain risk management, which includes the use of software agents, for data mining, integrated with agent based simulation platforms. This framework enables rapid data collection for simulation input, while also providing an intuitive simulation platform.

5 Reparable Item supply Chain Risk Measurement Framework

5.1 Overview

The primary difference between consumable and reparable item supply chains is that reparable items stay in the supply chain until deemed obsolete. Reparable items loop through the supply chain in a cycle of failures and repairs, which requires more resources and more extensive management due to the greater complexity. Thus, decision makers need different information to manage inventory and logistics, and need a whole other pool of knowledge of repair processes.

To the best of our knowledge, supply chain literature lacks published work in reparable item supply chain risk metrics. This chapter fills this gap, by providing a risk metrics framework specific to reparable item supply chains. Along with combining existing consumable and AF reparable metrics, we developed new metrics and enhancements to existing metrics. Since the Balanced Scorecard framework has proved successful in industry and the Department of Defense (DoD), we used its underlying structure, or categorization, for our reparable item metrics framework.

The AF logistics community uses the balanced scorecard perspective, but has modified the perspectives from Customer, Internal Business, Finance, and Innovation and Learning to be Warfighter, Logistics Processes, Resource Planning, and Innovation and Learning (AFMC 2005). Figure 10 provides the original scorecard designed for industry/commercial organizations that seek to make profit. Figure 11 provides the

modified scorecard developed under the Expeditionary Logistics for the 21st Century (eLog21) effort for Department of Defense (DoD) Logistics.

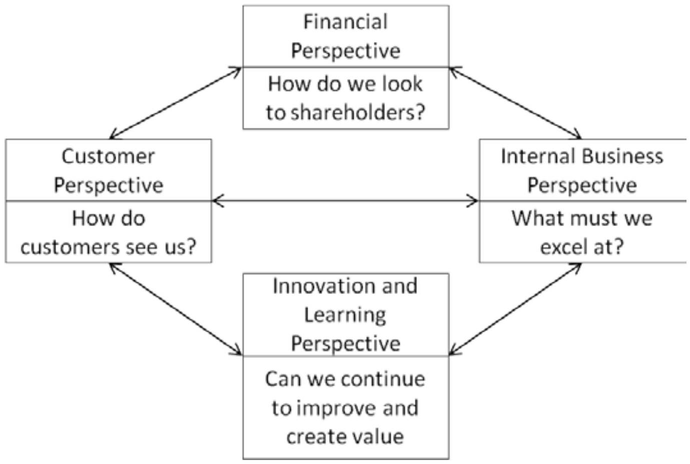


Figure 10 - Original Balanced Scorecard Performance Measures (Kaplan and Norton 1992)

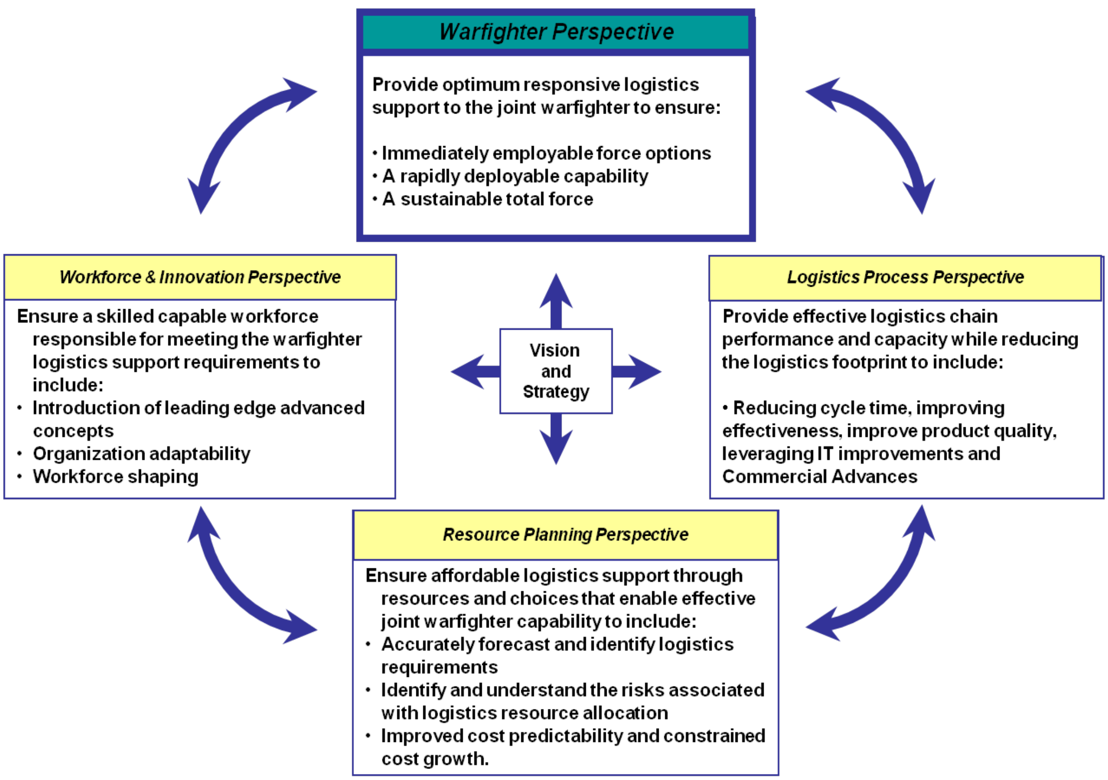


Figure 11 - Balanced Scorecard for DoD Logistics (DoD 2004)

Along with the balanced scorecard, another performance measurement category from Table 7 that aligns well with the AF is the decision-making levels, i.e. strategic, tactical and operational. However, these decision making levels are embedded in the balanced scorecard framework and are apparent when the scorecard is specialized for different levels of users. The remainder of this chapter discusses consumable item supply chain metrics, Air Force specific metrics, and our recommended reparable item risk metrics framework, and aggregation and disaggregation of metrics.

5.2 Consumable Item Supply Chain Metrics

This section provides performance and risk metrics found in literature on consumable items. Most of these metrics are listed in Chapter 2, but more detail is provided here and metrics are categorized according to the balanced scorecard framework. Customer, Processes, Finance, and Learning and Growth are the perspective categories for the commercial/industry balanced scorecard. Metrics that are not straightforward are discussed in the subsequent sections.

Table 13 - Consumable Item Risk Metrics

Customer Perspective	***Financial Perspective***	***Internal Business Perspective***	***Innovation and Learning Perspective***
fill rate (service level)	total supply chain cost	cycle efficiency (Brewer and Speh 2000)	warning capability (Craighead et al. 2007)
product/service availability	holding cost	product finalization point	product availability
customer perception of service	logistics cost	number of customer contact points (Craighead et al. 2007)	sales to inventory ratio (Kleijnen and Smits 2003)
number of "perfect orders"	backorder cost	structural reliability	ratio of product cost to material size (Gunasekaran et al. 2001)
stockout rate	percentage of targets achieved	resiliency	inventory level

Customer Perspective	***Financial Perspective***	***Internal Business Perspective***	***Innovation and Learning Perspective***
average duration of stockout	probabilistic financial risk (Barbaro and Bagajewicz 2004)	vulnerability	inventory cycle time
error rates	downside risk (You et al. 2009)	node criticality (Craighead et al. 2007)	flow rate (Chan and Qi 2003)
damage rates	value-at-risk (VAR) (Jorion 2002)	exposure (Manuj and Mentzer 2008)	inventory productivity (Chan and Qi 2003)
reliability	conditional-value-at-risk (CVAR) (Jorion 2002)	logistics index (Hausman et al. 2005)	inventory turns (Min and Zhou 2002)
order cycle time	cash-to-cash cycle time (Brewer and Speh 2000)	risk factor (Pai et al. 2003)	percentage of goods in transit
customer wait time	return on supply chain assets (Brewer and Speh 2000)	supply chain density (Craighead et al. 2007)	visibility (Caridi et al. 2010)
confirmed fill rate	variance of profits (Li and Zhou 2009)	supply chain complexity (Craighead et al. 2007)	number of shared data sets (Brewer and Speh 2000)
responsiveness	difference of variances of profits (Li and Zhou 2009)		product category commitment ratio (Brewer and Speh 2000)

5.2.1 ***Customer Perspective.***

To augment service level (i.e. fill rate), Kleijnen and Smits (2003) define confirmed fill rate as the percentage of orders delivered 'as negotiated,' where orders are renegotiated upon realization that the requested delivery is not feasible. To relate how effectively the supply chain is able to offer variety without unduly lengthening the time it takes to create this variety, Brewer and Speh (2000) present a metric of number of choices offered relative to response time. Responsiveness is a submetric of reliability, and is defined by Bhagwat and Sharma (2007) as timeliness and effectiveness to respond to customer order changes.

5.2.2 *Financial Perspective.*

Probabilistic financial risk is the probability that, across a range of scenarios, the real cost is higher than a certain target (Barbaro and Bagajewicz 2004). By reducing the probabilistic financial risk for a target, we can reduce the risk of having high costs (You et al. 2009). Downside risk is similar to probabilistic financial risk, but measures the variability between the real cost and the target cost for each scenario, rather than simply using a binary variable to indicate yes/no the real cost exceeds the target (You et al. 2009). As described in section 5.4.3.2, the concept of comparing metrics to a target under several scenarios can be helpful for non-financial metrics (e.g. delivery time, stockout rates, etc.).

Value-at-Risk is a category of risk metrics that describe probabilistically the market risk of a trading portfolio (Jorion 2002). Cash-to-Cash is essentially the average time frame to turn a dollar invested in raw material, labor, etc., into a dollar collected from a customer (Brewer and Speh 2000). Return on supply chain assets measures how efficiently the supply chain is coordinating the use of its assets, and is calculated by dividing consumer profitability by the average supply chain assets deployed during the period (Brewer and Speh 2000). Variance of profits and difference of variances of profits are used in analyzing supply chain risk at each node caused by pricing (Li and Zhou 2009).

5.2.3 *Internal Business Perspective.*

Exposure refers to the number of different types of risk events that occur in a given time period (Manuj and Mentzer 2008). Logistics index and risk factor are two

metrics that measure how these risks can affect the supply chain. Logistics index, which was developed by Hausman et al. (2005), combines corruption perception index, gross domestic product, transport time, cost, and distance. Risk factor is defined, by Pai et al. (2003), as the product of probability of threat occurrence, consequence, and value of asset.

Supply chain density refers to the average geographical spacing between nodes and number of dense areas within a supply chain (Craighead et al. 2007). A similar metric, defined by Craighead et al. (2007), is supply chain complexity, which is the summation of number of nodes and material flows (forward, backward, and within-tier).

5.2.4 ***Innovation and Learning Perspective.***

Visibility index is a metric of information translucency throughout the supply chain. This includes quantity of exchanged information and information quality, in terms of accuracy, timeliness, completeness, freshness, relevance, and accessibility (Caridi et al. 2010). One way of increasing visibility, and also eliminating redundancy and information lag, is information sharing and implementation of a central data set. Number of shared data sets relative to total data sets (Brewer and Speh 2000) measures the supply chains efficiency with data storage.

Product category commitment ratio measures the extent to which partnerships exist, and also measures the potential risk to which each partner is exposed within a supply chain relationship. This metric is calculated by dividing the percentage of the customer's product category needs that they bought from the seller by the percentage of

the seller's total product category sales that are sold to that customer (Brewer and Speh 2000).

Chan and Qi (2003) relate inventory level to inventory cycle time, by defining flow rate as the ratio of the two metrics. Inventory productivity refers to stock unit (storage space) utilization and working inventory rate, which is the percentage of working inventory to total inventory (Chan and Qi 2003). Inventory turns is the ratio of annual costs of goods sold to average inventory investment (Min and Zhou 2002). Most of the consumable metrics apply to reparable item supply chains, but there are additional metrics specific to reparable item supply chains. The next section reviews some of these metrics in context to Air Force specific metrics.

5.3 Air Force Specific Metrics

The end users of Air Force supply chain metrics are Air Staff (HQ USAF/IL), major commands (MAJCOM), and the Air Logistics Centers (ALC). Air Staff (HQ USAF/IL) strives to meet budgetary constraints, while ensuring metrics don't get worse. MAJCOMs strive to keep all readiness kits full and drive backorders to zero. The ALC's goal is to achieve the level of performance that is consistent with its funding level. (Leonard 2004)

With these goals, the Air Force (AF) uses metrics from industry/commercial sectors, along with metrics specific to its supply chain as a government organization. AF metrics as outlined by AFMC (2005) and AFMC (2003) are divided into two categories, namely performance measures and process indicators. A performance measure is data that indicates the strengths and opportunities for improvement in an organization, while a

process indicator is data that provides information about or contributes to the understanding of a process (AFMC 2003). Process indicators facilitate root-cause analysis and add additional meaning to performance measures, but are not formally monitored against set targets (AFMC 2005). Since the AF metrics fall into several perspectives of the balanced scorecard, as shown in Table 14, we discuss the metrics categorized by performance measure and process indicators instead of categorized by balanced scorecard perspective as in section 5.2. Along with our insights on additional metrics, the following sections paraphrase metrics as described by AFMC (2005).

Table 14 - Current AF Metrics (Balanced Scorecard Framework)

Warfighter Perspective	Resource Planning Perspective	Logistics Processes Perspective	Workforce & Innovation Perspective
MICAP Hours	NOR	AA	AA
CWT	IE	MICAP Incidents	TRV
Perfect Order Fulfillment	SE	MICAP Hours	
	TRV	Backorders	

5.3.1 ***Performance Measures.***

Aircraft Availability (AA) serves as the AF's primary performance measure and represents the percentage of time an aircraft is available for a mission. Total Non Mission Capable Supply (TNMCS) rate represents the percentage of time a weapon system cannot fly any of its assigned missions due to supply and/or maintenance conditions. This results in $AA = 1 - TNMCS$. A weapon system can be classified as fully-mission capable (FMC), non-mission capable (NMC), or partial-mission capable (PMC). Instead of strictly calculating AA based on NMC, the metric could be split into separate metrics of Operational Availability (OA) for FMC and PMC.

Mission Capable (MICAP) Hours is the measure of total time (in a month) consumable or reparable parts affecting mission capability are on backorder. A similar metric to MICAP hours can be applied to industry/commercial supply chains. Frequency of this metric may be more appropriate in days, weeks, quarters, etc. A related performance metric is Customer Wait Time (CWT). CWT measures the average time between placement of a customer order and delivery of that order to the customer. Shorter CWTs may indicate a large number of backorders since these backorders will not adversely impact CWT until they are filled. On the other hand, longer CWTs may indicate a problem has been resolved resulting in a large number of backorders being filled, which drives CWT up. Any detailed analysis using CWT should look closely at both short and long times. Tracking average age of backorders along with CWT will provide more insight as to true performance, reducing the lag effect from old backorders. A metric could be included that combines CWT and average backorder age. Similarly, a metric that includes CWT and the number of backorders filled can help clarify CWT.

One additional performance metric is Net Operating Result (NOR). NOR measures the difference between revenue and expenses from operations for an activity group in relation to a defined standard. For example, the Supply Management Activity Group strives to achieve a NOR that breaks even over a two-year budget cycle.

5.3.2 ***Process Indicators.***

MICAP incidents provide a simple count of the MICAP requisitions in process for a given month. This number includes all MICAP transactions that were open for any time during the month.

Total Requirements Variance (TRV) compares actual Retail Due-Outs (MICAPS, Awaiting Parts, Delayed Discrepancy and Due-Outs to Maintenance backorders) versus Expected Backorders (EBOs) for a specific part. The TRV identifies high variance parts that are either in a significant state of shortage at specific locations or that have been over-allocated.

Issue Effectiveness (IE) is the percentage of time base supply immediately satisfies a requisition with stock off the shelf, as shown in Equation (1). Stockage Effectiveness (SE), depicted in Equation (2), is the percentage of time base supply satisfies a requisition with stock off the shelf for items with an authorized stock level (SE is a subset of IE). Low issue effectiveness may be reasonable depending on the SE value. The two metrics must be viewed in tandem.

$$IE = \frac{Issues}{(Issues + BO_{2D} + BO_{4W})} \tag{1}$$

$$SE = \frac{Issues}{(Issues + BO_{2D})} \tag{2}$$

Where Issues is a count of parts supplied off the shelf, BO_{2D} is the backorders authorized to stock, and BO_{4W} is the backorders not authorized to stock.

Backorders measure the number of demands placed on the supply system not immediately satisfied from existing inventory. A metric for average age of parts clarifies whether backorders are occurring because of depleted serviceable assets or that there are simply process issues in the supply chain. Some indication as to the percentage of parts that are considered “new” could also provide insight. That is, tracking age of parts compared to some degradation curve provides information on expected fleet performance.

Balestreri and McDoniel (2002) discuss the Due-in-from-maintenance (DIFM) metric, which measures the work in process inventory. This metric provides insight to pipeline inventory and whether inventory will be replenished soon or backorders will soon be filled. Readiness degraders and readiness-critical measures are also discussed by Balestreri and McDoniel (2002). The idea is items that are critical to the mission, i.e. readiness degraders, should hold greater importance in supply chain management than other items. These metrics place more emphasis on items that are critical to the mission.

5.4 Recommended Reparable Item Risk Metrics Framework

This section presents a reparable item supply chain risk measurement framework that combines consumable metrics, Air Force metrics, and new metrics developed to enhance existing metrics such that further information can be gleaned.

5.4.1 *New Metrics.*

Combining CWT with average backorder age or number of backorders filled, as mentioned in section 5.3, enables better insight to the cause of short or long CWT. Other new metrics mentioned in section 5.3 include operational availability (OA) split into FMC and PMC, and percentage of parts considered "new." The former is discussed in greater detail in this section. The latter metric tracks age of parts compared to some degradation curve, which can help explain increased failures and poor supply chain performance.

AA is the AF primary performance measure and reflects the percentage of time a weapon system is fully-mission capable. A weapon system can also be classified as partial-mission capable (PMC), so capturing the percentage of time a weapon system is

PMC could provide knowledge to supply chain performance. With the basic AA metric, PMC and FMC were combined, blurring the distinction between good management of mission critical and non-mission critical items. Therefore, we propose to split AA into two operational availability (OA) metrics. Namely, OA_{FMC} and OA_{PMC}, which are calculated according to Equations (3) and (4).

$$OA_{FMC} = 1 - \frac{TNMC\ time - \ PMC\ time}{Total\ time} \tag{3}$$

$$OA_{PMC} = \frac{PMC\ time}{Total\ time} \tag{4}$$

OA_{FMC} provides a better measure than AA of a weapon system's total availability to fly any mission. While OA_{FMC} is a stand-alone metric, OA_{PMC} should be viewed in tandem with OA_{FMC} to avoid misconception of total supply chain performance.

Metrics for average age of backorders (BOs) and number of backorders filled are useful supply chain performance measures by themselves, but they can also augment CWT analysis. Time average number of backorders (TAB), as depicted in Equation (5), provides the average number of active backorders, where BO(t) is the number of backorders at any time instance t. An increasing trend in average number of backorders serves as a signal for potential supply chain problems. Similarly, the simple average age of backorders tracked over time shows trends leading to significant supply chain performance degradation. However, some backorders might be of less concern if the items are non-mission capable. Therefore it is recommended to capture mission criticality (MICAP) and non-mission criticality (non-MICAP) when calculating backorder metrics. For example, Low values of TAB_{MICAP} illustrates good management of mission critical

items, while high values show that processes need improvement or additional funding is necessary for mission critical items.

$$Time\ Avg\ Number\ Backorders = \frac{\int_0^{Total\ time} BO(t)}{Total\ time} \tag{5}$$

Another backorder metric, shown in Equation (6), is the ratio of actual number of backorders to expected number of backorders. The expected number of backorders is the forecasted value, so ideally we want the actual number to be as close as possible to the forecasted value (i.e. BO ratio = 1). Although a value of 1 is ideal, values less than 1 are better than values greater than 1 because the supply chain is performing better than expected. Deviations from the forecasted value can cause problems throughout the supply chain, such as planned inventory.

$$BO\ ratio = \frac{Actual\ number\ of\ backorders}{Expected\ number\ of\ backorders} \tag{6}$$

In addition to backorders, other key performance metrics for a base or depot are inventory related measures. The ratio of parts' inventory cost to its size can be used in trade-off-analysis when storage space is a constraining factor. Large items usually have a large inventory holding cost, but this is not always true with electronic parts. An example scenario where this metric would be useful, is for a large part with low cost. Similarly, combining probability of repair at the location of inventory and repair time can depict locations in the supply chain network that need to be further analyzed. Average age of reparables, or percentage of reparables considered "new," can augment supply chain metrics to clarify if poor performance is due to deterioration or supply chain processes and policies. A similar metric, is the average time an item spends on the shelf between usages, which is a variation of the cash-to-cash metric.

Including a metric for resource requirements (e.g. including resources for shipping and repair) provides insight to process metrics. For example, items with low repair times that require a large number of resources to ship and repair the item could be more susceptible to supply chain risks. That is, resources might be allocated elsewhere during a non-local disruption, or resources might be compromised during a local disruption. Thus, monitoring and managing items requiring greater resources could reduce impacts if disruptions do occur.

As previously discussed, inclusion of mission criticality in the metrics provides much greater insight to supply chain performance. Whether splitting metrics into separate mission criticality categories, or altering metric calculations to include weighting factors, it is strongly suggested to augment metrics with mission consideration.

5.4.2 ***Reparable Item SC Risk Metrics Framework.***

The American Production and Inventory Control Society (APICS) advises organization to focus on five (+/- 2) metrics to avoid metric-overload (AFMC 2003). However for our research we want to provide a general list of metrics that can be narrowed down for specific users. Our risk metrics framework for reparable item supply chains is provided in Table 15. AF metrics are in normal text, commercial/industry metrics in italics, and new metrics are bolded. We demonstrate use of this framework with an application in Chapter 6.

5.4.3 ***Monitoring and Managing Risk Metrics.***

A primary recommendation for the reparable item supply chain item framework is to focus on mission capable items. This can be accomplished by reporting metrics

separately for mission critical and non-mission critical items. Measurement frequency and comparatives, or target values, are the key factors in monitoring and managing performance and risk metrics. Bias factors and metric aggregation are also key factors in successfully implementing performance and risk metrics frameworks. Details for specific metrics are not provided because each supply chain will be handled differently and various levels of management use the metrics differently.

Table 15 - Reparable Item Risk Metrics Framework

Customer Perspective	Resource Planning Perspective	Logistics Processes Perspective	Innovation and Learning Perspective
MICAP hours	NOR	AA	AA
CWT	IE	MICAP incidents	TRV
Perfect order fulfillment	SE	MICAP hours	*Working inventory rate*
NMCS/NFMCS rates	TRV	Backorders	*Visibility*
Error rates	*Downside risk*	*Working inventory rate*	*Warning capability*
Responsiveness	*Return on assets*	*Stock unit utilization*	*Inventory productivity*
Operating availability (OA_{FMC}, OA_{PMC})	**Parts' inventory cost to size**	*Product finalization (for repair kits)*	**Operating availability (OA_{FMC}, OA_{PMC})**
	Probability of repair * repair time	*Cycle time*	**Backorder (BO) ratio**
	Avg. age of reparable	*Agility*	**Avg age of reparable**
	% of reparable that are "new"	*Vulnerability*	**% of reparable that are "new"**
		Resiliency	
		Risk factor	
		Node criticality	
		Percentage of goods in transit	
		Operating availability (OA_{FMC}, OA_{PMC})	
		Time avg. number backorders (TAB)	
		Avg. age of backorders	

5.4.3.1 Measurement Frequency.

Selection of proper metrics is difficult, but often collection and interpretation of metrics can prove difficult as well. An example where improper analysis of risk metrics led to supply chain disruption, is a company described by (Manuj and Mentzer 2008) in which metrics were analyzed over too short of a time period subsequently leading to defective parts and an approximate loss of 15% of the company's bottom-line profit.

Tracking performance metrics through time enables trend analysis that can uncover patterns leading up to a supply chain problem or provide insight to supply chain improvement. Several policies exist for determining when and how often metrics should be measured. Measurement frequency can be based on the expected rate of change in the result (Frost 2000), importance of the particular process in the overall organization, or lead-time required to change the course of action (Leonard 2004). We recommend for reparable item supply chains, measurement frequency should be based on mission criticality, repair time, probability to be repaired, and/or repair time variance. A mission critical item that takes significantly longer to repair, or has large variance, should be more closely monitored to ensure timely corrective action. Non-mission critical items, or quick turn items, do not require as close monitoring. In fact, over-correction and constant unnecessary changes from corrective action can result from measuring too frequently. Most often, reporting frequency is determined by upper management schedules, and not necessarily the most beneficial frequency.

5.4.3.2 Comparatives / Targets.

Comparatives are defined as the benchmarks or standard values used to judge metrics against, which then translates into supply chain performance and leads to

actionable areas. The three broad types of comparatives are internal, external and theoretical, with the additional comparative of targets established as part of the budgetary process (Leonard 2004). Individual portions of an organization seeking to improve specific problem items or areas that have been identified to be affecting a performance measure may set internal targets (AFMC 2003). However, it is imperative that organization-wide targets are not ignored because this could lead to sub-optimization. Augmenting the comparatives with variance indicators provides greater insight to metric performance. Air Force Materiel Command utilizes a color-coding scheme that signals light green for a metrics within ±2% from target, yellow for values less than -2% and greater than -4% of target, red for values less than -4%, and dark green for values greater than +2% (AFMC 2003). We recommend tracking improvement/regression along with variance of the metrics over time to broaden trend analysis. Slow regression of a metric value over time may not be of great concern to supply chain managers, but a rapid regression over time should be immediately analyzed.

5.4.3.3 Metrics Challenges.

In striving to maximize AA, field maintenance personnel will sometimes employ practices that can skew, corrupt and bias supply chain metrics (AFMC 2003). These practices include: removing parts from one weapon system to fill a demand on another, i.e. cannibalization; getting the needed part from another base, i.e. lateral supply; and use of readiness spares packages as an extension of the warehouse to fill demand, i.e. non-project-coded kit issues (AFMC 2005). Other, real world factors that can skew metrics are flying hour variance and total requirements variance. Action should be taken to

reduce the impact of these real world factors on the metrics. This can be achieved by tracking these practices and occurrences in order to adjust metric calculations.

Challenges that arise when defining the metrics to use in the framework include correlation between the metrics, lag, and predictability. To ensure certain aspects or problems are not over-emphasized by using several metrics depicting the same supply chain performance aspect, correlation among metrics must be analyzed. Lag analysis should be performed to determine actual sources of supply chain risks and ensure that over time the right targets are analyzed. Lastly, it is ideal to define the metrics in a way that enables forecasting capability. This can provide greater management capability, as well as decrease risk and improve supply chain performance.

5.5 Aggregation and Disaggregation of Metrics

Since metrics are used at various levels of supply chain management there must be some means for aggregation and disaggregation. The direct approach for aggregating metrics is to roll up metrics from lower level of management. For example, AA calculated at each base can be aggregated to obtain AA for the entire fleet. A more labor intensive but exact approach to obtaining metrics at various supply chain levels is to calculate metrics at all levels from raw data, instead of aggregating data. This method requires data collection at each level, not just the lowest level of supply management.

5.6 Summary

Our research is the first to publish a formal risk metrics framework for reparable item supply chains along with new metrics designed for the AF supply chain. A metrics framework specific to reparable item supply chains is necessary because compared to

consumable item supply chains, reparable items have greater complexity, which requires more resources and more extensive management. Decision makers need different information to manage inventory and logistics, and a whole other pool of knowledge of repair processes.

6 Application

6.1 Goal

To demonstrate our modeling framework, we applied it to a portion of the F-16 supply chain, specifically the landing gear assembly. Java coded software agents randomly collect data points from a local database, calculate input parameters, and provide this data to an agent based model in AnyLogic simulation software. The simulation model demonstrates variable resolution agent based modeling and simulation (ABMS) by modeling three levels of resolution, as depicted in Figure 12. Within the F-16 supply chain we focus on forty-five parts that are categorized into three Federal Stock Classes (FSCs) within the landing gear subassembly. All forty-five parts are reparable items. Lastly, model output is used to calculate risk metrics, and aggregated risk metrics.

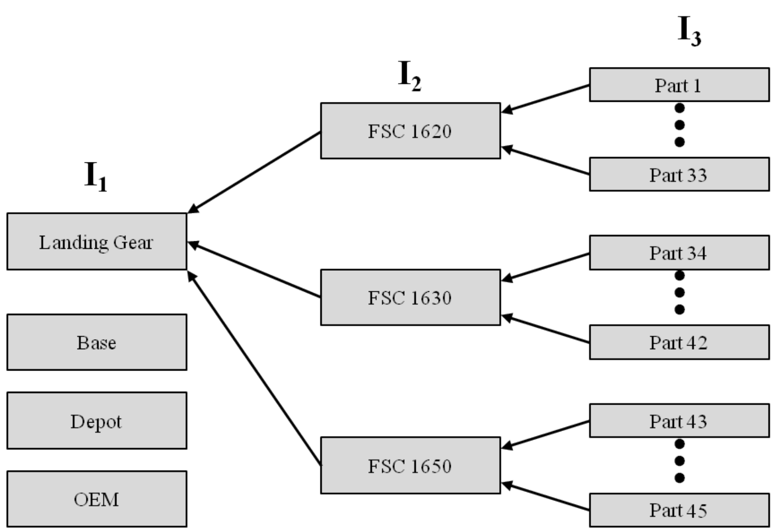


Figure 12 - Application Model Active Agents

The model was used to analyze the risk of the Department of Defense (DoD) reducing funding for aircraft availability (AA). Reduced funding is captured in the

number of parts repaired and the inventory policies at each location. Each base and depot holds a target level of parts in inventory. Thus, we analyze mission capability and supply chain performance with lower inventory policies throughout the supply chain. Along with the risk of reducing funding for AA, we analyze the impact of different supply chain disruptions. This is modeled by creating extra delays in the supply chain processes. For example, there could be a terrorist attack that delays transportation of parts from the base to the depot.

Furthermore, we consider two aggregation techniques for lower resolution model input. The first technique is to analyze the raw data prior to running the modeling framework and using aggregation models on this data to calculate the input for the lower resolution inputs. The second technique is using high resolution simulation output to calculate lower resolution input. This analysis demonstrates the benefits and difficulties of variable resolution ABMS.

6.2 Model Assumptions

Supply chain aspects that exceed the scope of this modeling effort include cannibalization, non-project-coded kit issues, and lateral supply (i.e. base-to-base transfers). For this analysis, it is assumed that these practices do not exist in the F-16 supply chain and all parts are received from base stock or the depot. We also assume constant flight hours for each quarter. In the true system, flight hours vary each quarter according to mission requirements, which affects mean time to failure. Also, we assume there is no difference between scheduled repairs and random failures. Data limitation was the key factor in exclusion of these aspects.

After initial pilot runs it was determined that independent failures caused unrealistic aircraft availability. Subject matter experts confirmed that there are dependencies between parts, however this information was not available. Therefore, we grouped parts into dependent groups where a single part fails and triggers the others to fail.

6.3 AB Model

Active agents within the model are Parts, FSCs, Landing Gear, Bases, Depots, and the Original Equipment Manufacturer (OEM). Resolution level is set by the user in the main model via a variable. A value of three results in Part agents being activated, value of two activates FSCs, and a value of one activates the Landing Gear agents. Furthermore, switches in the model use the resolution value to execute certain lines of code to ensure the proper logic is executed. For example, output is collected in different ways for FSCs and Landing Gear based on the resolution level.

Depending on the level of resolution, Parts, FSCs, or Landing Gear agents trigger a failure according to its MTBF. When a failure occurs an order and the broken reparable are sent to the appropriate base supply. Bases and depots process orders and backorders at the beginning of each day. If base supply has available inventory, then a working reparable is sent from inventory back to the original broken agent. The base then decides whether to locally repair the broken reparable or send it to the corresponding depot. If the base fixes the broken reparable, then it is added to inventory after the mean time to repair at the base. When the broken reparable is sent to the depot and the base requests a replenishment part, the depot sends a working reparable from inventory, or repairs the

broken reparable and sends it back to the originating base. Broken reparables that are not fixed at the base or depot level are condemned and a replenishment order is sent to the OEM if the target stock level is reached. Note that we use a single OEM agent because we are not collecting any statistics specific to each OEM. We are simply modeling a delay for production and shipment of the reparable. The OEM agent sends a new reparable to the originating depot, which is added to the depot inventory.

Our model does not include detailed decision logic within agent behavior. This was beyond project scope for our demonstration purpose. Logic could be added to agent behavior to respond to supply chain disruptions (e.g. find a different source of supply). Currently it does not make sense to run the model with different resolutions of time because days are sufficient for model fidelity at each of the three levels of entity resolution. Furthermore, our model runs at a single level of process resolution because detailed processes were beyond the scope of this demonstration. The model runs for two years simulated time to align with historical data used in input analysis, thus making it a terminating simulation.

6.4 Data

Two years of historic data was used due to data availability and the fact that the Air Force uses eight quarters of historic data to forecast the number of parts to purchase and repair for the future quarter. It is assumed that each quarter had the same number of flight hours. The Logistics, Installations and Mission Support Enterprise View (LIMS-EV) database, D200 Requirements Management System, and subject matter expert (SME) estimates are the sources of the data. Data outliers were removed prior to analysis,

along with parts that had no repairs at the depot or base levels (i.e. repair at this station (RTS) ≤ 0 or non-repair at this station NRTS ≤ 0). After eliminating these parts there were 45 remaining reparable parts, which come from three Federal Stock Classes:

FSC 1620: Aircraft Landing Gear Components (33 parts)

FSC 1630: Aircraft Wheel and Brake Systems (9 parts)

FSC 1650: Aircraft Hydraulic, Vacuum and De-icing System Components (3 parts)

Table 16 lists the input and output required for each type of active agent. Mean time between failure and repair time at the base was calculated from base requisition data from the Air Force Logistics Studies Workshop (AFLSW). Maintenance time, which is the time to install the part on the aircraft once the working part is received from base supply, was estimated by subject matter experts. It was estimated with equal probability (i.e. 25% of the time) to take 2, 8, 12, or 24 hours to install a part on the aircraft. Shipment time between base and depot, percent repaired and percent condemned at the base were collected from rollup data in D200. The rollup data is an average of the raw data, which we could not access. Percent fixed at the depot and depot repair times were provided from roll-up data from LIMS-EV. Subject matter experts calculated stock levels by running a function, within D200, that considers flight hours, operational stock, non-operational stock, price, and so on.

Distributions for input variables were determined manually in a preprocessing step prior to running the modeling framework. Within JMP software distributions were fit and goodness-of-fit were tested. From this input analysis and common theoretical applications of the distributions, it was determined that a lognormal distribution is the

best fit for repair times and an exponential distribution is best fit to model mean time between failures.

Table 16 - Application Model Input and Output

<table>
<tr><th colspan="2">Model Input</th><th colspan="2">Model Output</th></tr>
<tr><th>Active Agent</th><th>Input Variable / Parameter</th><th>Active Agent</th><th>Output Parameter</th></tr>
<tr><td rowspan="8">Part/ FSC/ Landing Gear</td><td>Mean time between failure</td><td rowspan="4">Part/ FSC/ Landing Gear</td><td>Customer wait times (CWT)</td></tr>
<tr><td>Mean time to repair at base & depot</td><td>Operational Availability (AA)</td></tr>
<tr><td>Maintenance time</td><td>Number of Failures</td></tr>
<tr><td>Shipment time to depot & OEM</td><td>Mean time between failure</td></tr>
<tr><td>Manufacture time</td><td rowspan="5">Base / Depot</td><td>Number of reparables fixed</td></tr>
<tr><td>Percent fixed at base level</td><td>Average # Backorders</td></tr>
<tr><td>Percent fixed at depot level</td><td>Average Backorder age</td></tr>
<tr><td>Percent Condemned</td><td>TAB</td></tr>
<tr><td>Base / Depot</td><td>Target Inventory Level</td><td>Total # Backorders</td></tr>
</table>

Selection of which base data to use as baseline MTBF input was performed by comparing average aircraft availability output over forty replications. Luke AFB had data for all 45 NSNs, followed by Nellis AFB with 41 NSNs, and Daluth ANG with 35 of the NSNs. For the missing NSNs data was used from Luke AFB. During pilot runs it was determined that unusually low landing gear availability was caused by a single part type. This part is condemned at the base with 100% probability and has base and depot stock levels of 2, and 9, respectively. We deemed this outlier in percent availability a data quality issue and set inventory levels (i.e. stock levels) for this part to be unlimited. From the resulting landing gear availability, as shown in Table 17, Luke AFB had the highest aircraft availability. Therefore we use MTBF data from Luke as the baseline scenario. As a note Luke AFB is a training base, so results may vary with MTBF from other bases.

Table 17 - Base MTBF Comparison

Base	Avg % Availability
Luke	95.07 ± 0.44
Daluth	90.11 ± 1.14
Nellis	70.68 ± 1.76

Decrease in funding for the F-16 weapon system is the first alternative system we selected to analyze against our baseline simulation. Essentially we want to analyze the risk to the supply chain when funding is cut. Base and depot stock levels, or target inventory levels, were calculated in D200 for a 5% and 10% drop in funding. Since there was no difference in stock levels for the 45 selected NSNs, we used the average percent drop over all parts provided in the data. This resulted in a 1.63% and 2.57% drop in base stock level and 0.94% and 1.73% drop in depot stock level for 5% and 10% funding drop, respectively.

All data was entered into an Access database to serve as a surrogate source for real Air Force data sources. This database is used by software agents to collect simulation input, as discussed in the following section.

6.5 Software Agents

Software agents were coded in Java along with imported libraries including Microsoft Access libraries. Each software agent collects a sample of values for each of the forty-five parts for a specific simulation input variable from an Access table. Input parameters (i.e. mean and standard deviation) are calculated with this sample and written to a comma separated values (CSV) text file. Although, the software agents are not directly linked with agent based simulation agents at this time, we are showing the applicability of the theory by having an intermediate step of writing to a CSV file. Input

parameters calculated by software agents include mean and standard deviation of repair time at the base and depot, and mean time between failures.

Mean and standard deviation for repair times were calculated using functions from the imported libraries. If there are less than thirty values available in the database, then the parameters are calculated using all available data values. When there are more than thirty values available, a random sample of thirty is collected to calculate parameters. Since the lognormal distribution function call in AnyLogic requires the mean and standard deviation of the included Normal distribution, another set of calculations were performed before writing the values to the CSV file. The calculations are depicted by Equations (7) and (8), where mean and stDev have already been calculated and σ and μ are the necessary lognormal parameters.

$$\sigma = \sqrt{ln\left(\frac{stDev^2}{e^{2\ln(mean)}} + 1\right)} \tag{7}$$

$$\mu = \frac{2\ln(mean) - \sigma^2}{2} \tag{8}$$

Mean time between failure is calculated by taking the inverse of daily demand requirement (DDR) per aircraft, as depicted in Equations (9) to (11). DDR is the sum of requests from base stock for a specified time period divided by the number of days in that time period. This is divided by the number of aircraft to get the DDR per aircraft. The inverse of DDR per aircraft provides an estimate for mean time between failure for each part.

$$DDR = \frac{\sum number\ requested}{Number\ of\ Days} \tag{9}$$

$$DDR\ per\ Acft = \frac{DDR}{\#\ acft\ at\ base} \tag{10}$$

$$MTBF = (DDR\ per\ Acft)^{-1} \tag{11}$$

Air Force program averages and best estimates provided by subject matter experts are also pulled from the Access database by software agents. Since there is a single data point for each of these input variables, the software agents simply pull the single value and output this to the CSV file. Single point input variables include shipment time between base and depot, manufacture time, percent fixed at depot, percent fixed at base, and percent condemned at base.

6.6 Verification and Validation

Verification was performed via animation, tracking event execution and performing a trace, analysis of random variate generation, and analysis of output measures. Analysis included numeric calculations along with plotting performance measures over time. Animation was used primarily in verifying dependent failures and corresponding update of operational status for FSCs and landing gear agents.

The system captured by our simulation model is an abstraction of a small portion of a complex real world supply chain process covering bases throughout the world and hundreds of thousands of different parts. SMEs from the AFGLSC and bases and depots responsible for the data used in our simulation were consulted during model development to ensure we reasonably captured the real world processes being included in our model. Since we are modeling an abstraction of a specific subsystem of the F-16, our availability numbers and other metrics are not directly comparable to real world results. However, discussions with SMEs regarding the interaction of agents in our model and simulation

output, provided face validity for the modeled portion of the AF supply chain in our simulation. Therefore our model serves as an effective demonstration of our overall simulation framework to examine supply chain risk.

6.7 Results

The baseline model represents the modeled supply chain with no disruptions and inventory levels for AA funding level at the time of data request. With the baseline model we test the effect of two types of supply chain disruptions on risk metrics. To test the effect of reduced funding, AA is reduced by 10%. At this reduced funding level, we run scenarios without supply chain disruptions and scenarios with supply chain disruptions. Furthermore, all scenarios are run at two levels of resolution. Responses for the analyses, includes aircraft availability (AA), customer wait time (CWT), time average number of backorders (TAB), average backorder age, total number of backorders, and average number of backorders filled. It should be noted, that while some of our analysis compares multiple measures of effectiveness we do not adjust the level of significance for simultaneous confidence intervals, but rather use individual confidence intervals. All results are for forty replications, which provided us with output data that met required distributional assumptions along with acceptable standard errors.

6.7.1 *Initialization Period.*

At the start of each simulation run the inventory level at the bases and depots is set to the target stock levels, there are no orders or backorders in the system, and all part, FSC, and landing gear agents are working. Rather than make assumptions for initial conditions we used Welch's procedure to calculate an intelligent initialization period.

Average aircraft availability and average wait time output was collected from five replications of the baseline scenario, with run lengths of 2000 days. Moving average was calculated with windows of 1, 5, 50 and 100 data points. Figure 13 shows plots for average percent availability and average wait time for a window of 100. These plots indicate an appropriate initialization period of about 500 days. Therefore, code was added to the simulation model to clear collected output and begin the 200 day simulation run after day 500.

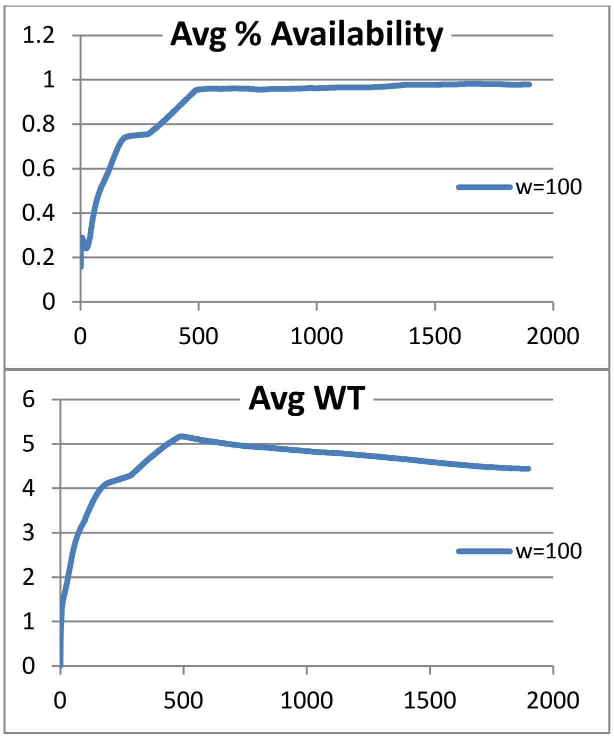


Figure 13 - Initialization Period Plots

6.7.2 ***Decrease in Aircraft Availability Funding.***

Statistical tests were performed in JMP software to compare baseline output to the 10% drop output. The difference in means between the baseline output and the 10% drop output along with 95% confidence intervals of various metrics are provided in Table 18. Statistical assumptions were verified for analysis in this chapter, but are not detailed in

this document. Statistically significant differences are found in average percent availability, wait time, time average number of backorders at a base, backorder age at a base and a depot, number of backorders at a base, number of backorders filled at a base, and the total number of backorders at all bases. Although there is a statistically significant difference, note that the practical difference between the values is often inconsequential. For example, the average percent availability drops less than 1% from the baseline. It makes sense that the 10% drop in aircraft availability funding results in less than 10% drop in our average percent availability output because we are only modeling a portion of each F-16 aircraft, and only a portion of the F-16 fleet.

Table 18 - Output for Baseline Funding versus 10% Drop

Performance Metric	$M_{Baseline}$	$M_{10\%Drop}$	$M_{Baseline} - M_{10\%Drop}$	Half-length	Confidence Interval
Avg. % Availability	95.15214	94.19480	0.9573	0.6343	(0.3230, 1.5917)*
Avg. WT (days)	1.84457	2.07418	-0.2296	0.1470	(-0.3766, -0.0826)*
Avg. # Fixed at Base	210.90833	208.74167	2.1667	5.4957	(-3.3290, 7.6623)
Base TAB	0.20605	0.33907	-0.1330	0.0773	(-0.2103, -0.0558)*
Base Avg. BO Age (days)	25.19514	29.55066	-4.3555	1.6006	(-5.9561, -2.7549)*
Avg. # BO at Base	7.31667	13.23333	-5.9167	2.6354	(-8.5520, -3.2813)*
Avg. # BO Filled at Base	7.46667	13.53333	-6.0667	2.6214	(-8.6880, -3.4453)*
Total # of BOs at Bases	21.95000	39.70000	-17.7500	7.9061	(-25.6561, -9.8439)*
Avg. # Fixed at Depot	259.32500	257.96250	1.3625	9.5104	(-8.1479, 10.8729)
Depot TAB	1.25763	1.46698	-0.2093	0.2222	(-0.4315, 0.0128)
Depot Avg. BO Age (days)	77.81116	82.11869	-4.3075	3.8276	(-8.1351, -0.4799)*
Avg. # BO at Depot	3.31250	3.01250	0.3000	0.9182	(-0.6182, 1.2182)
Avg. # BO Filled at Depot	6.96250	7.27500	-0.3125	1.0945	(-1.4070, 0.7820)
Total # of BOs at Depots	13.92500	14.55000	-0.6250	2.1889	(-2.8139, 1.5639)

* Represents statistically significant difference at 95%

Other insights can be drawn from the simulation output. For the baseline scenario, average number of backorders at the base, 7.32 backorders, seems large compared to the time average number in backorder (Base TAB), 0.21 backorders. This is because average

number of backorders is an average of all existing backorders over the entire two year period, while TAB is the estimate of number of backorders at any point in time within the two year period. Thus, TAB is a more insightful metric to determine day to day performance of the supply chain. The average age of backorders at the base shows that the few items in backorder at any point in time will be in backorder on average 25 days for the baseline scenario.

6.7.3 ***Lower Resolution and Aggregation Models.***

There are two methods for defining the aggregation models for different levels of resolution. Various mathematical formulas or models can be used to aggregate input data from existing resolutions as well as direct use of output from higher resolution simulations. In this section, we use both techniques to assess the significance of selecting the wrong aggregation models.

Simulation output captured from the resolution-three model is used as the true measure for the resolution-two model. That is, repair times, mean time between failure, shipment times, and percentages for condemnations and repairs by individual parts are captured for FSC agents and averaged to form input for the resolution-two model. This is called the Direct Method (DM) for determining values for the aggregated model. We picked six simple aggregation models and tested their output against the output from the DM model to demonstrate this piece of our framework. For more detailed discussion of these and more sophisticated aggregation methodologies see Rodriguez (2008). Average, maximum, and minimum of resolution-three inputs were the first three aggregation models tested, followed by three different mixtures of these aggregation models. Mixture

1 took the maximum values for process parameters (i.e. repair times, shipment time, manufacture time), average of percentage parameters (i.e. percent fixed and percent condemned), and minimum of MTBF and stock levels. This mixture stemmed from logic that the parts are combined into a single FSC. Mixture 2 is similar to mixture 1, but with an average MTBF instead of minimum, and mode for stock levels instead of minimum. Lastly, mixture 3 took the maximum of process parameters, average of percentages, average MTBF, and the median for stock levels.

Table 19 provides the 95% confidence interval comparisons with the Direct Method. All aggregation models result in statistical difference from the DM scenario. However, the confidence intervals are small, so we chose to rank order the aggregation models by how close their point estimate is to the DM scenario. Mixture 1 and Minimum were not included in this ranking because of their large difference in output from the DM scenario. For baseline funding the best aggregation model is Mixture 2, followed by Mixture 3, Average, and Maximum.

Table 19 - Average Aircraft Availability for Aggregation Models

g	Aggregation Model	$\lvert\overline{M_g} - \overline{DM}\rvert$	Half-length	Confidence Interval
1	average	3.5513	0.1315	(-3.6829, -3.4198)*
2	max	3.7207	0.1314	(-3.8520, -3.5893)*
3	min	62.7613	0.9718	(61.7895, 63.7331)*
4	Mixture1	91.7288	0.4087	(91.3201, 92.1375)*
5	Mixture2	3.3693	1.1005	(2.2688, 4.4698)*
6	Mixture3	3.5476	0.1317	(-3.6794, -3.4159)*

* Represents statistically significant difference at 95%

6.7.4 *Disruption Scenarios.*

To assess supply chain risk we simulated two types of generic disruptions. A process disruption at the base represents a delay in processing orders and backorders and delay in repairing broken parts. Transportation disruptions represent a delay in shipping broken parts and repaired parts between a base and depot. Essentially during the disruption period no items move between the base and depot. Initially a disruption length of seven days was tested, but no statistically significant difference appeared in the results, so we ran the scenarios with thirty day disruptions. Each disruption occurs 120 days after the initialization period. Both types of disruptions were tested at all the bases to determine if some bases are more sensitive to disruptions. Furthermore, each disruption scenario is tested at the decreased funding level to determine if disruptions cause a greater impact when funding is less. The scenarios tested are depicted in Table 20.

Table 20 - Supply Chain Disruption Scenarios

MTBF Input	Processes at the Base		Transportation between base & depot	
	Base Disrupted	Disruption Length (days)	Base Route Disrupted	Disruption Length (days)
Baseline	--	--	--	--
Baseline	0	30	--	--
Baseline	1	30	--	--
Baseline	2	30	--	--
Baseline	--	--	0	30
Baseline	--	--	1	30
Baseline	--	--	2	30
10% Drop	--	--	--	--
10% Drop	0	30	--	--
10% Drop	1	30	--	--
10% Drop	2	30	--	--
10% Drop	--	--	0	30
10% Drop	--	--	1	30
10% Drop	--	--	2	30

Since the primary measure of effectiveness is aircraft availability, we decided to perform a screening step using AA to determine which scenario to show more detailed performance measures. Figure 14 shows no statistically significant difference between the baseline scenarios, with each independent interval capturing the mean of 5-6 of the other scenarios. Bonferroni intervals would be even wider and show more overlap. For screening purposes we can clearly focus on the 10% funding drop scenarios, where we observed statistically significant difference between the process disruption scenarios. Therefore, decreased funding results in greater supply chain risk because different disruptions can significantly impact aircraft availability. It should be noted that a 10% decrease in funding level does not result in a 10% decrease in percent availability, as depicted by the baseline and 10% drop scenarios without disruptions. This is as expected, because we are only modeling the landing gear portion of the aircraft.

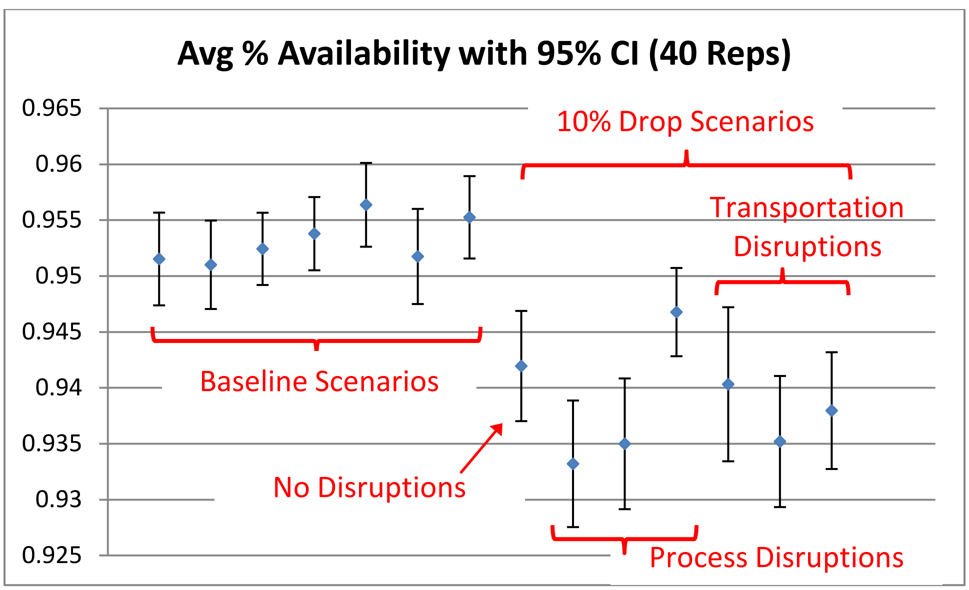


Figure 14 - Average Aircraft Availability for Supply Chain Disruption Scenarios

6.7.5 *Detailed Analysis for a Single Base.*

Other performance measures can be analyzed for each scenario, but we demonstrate this detailed analysis for two scenarios. These scenarios capture the two types of disruptions for a single base, base 2, with the 10% drop in funding. Some of the new metrics discussed in Chapter 5 could not be captured in the simulation model because sorties, or flight hours, were beyond the scope of our demonstration. Furthermore, mission criticality of the parts was not available, so metric augmentation was not feasible either.

The model was first run at the resolution-two level for both disruption types. Results, provided in Table 21, show that only average wait time has statistically significant difference between the two disruptions scenarios. However, the difference in the values is small, so practically speaking there is no difference between the two systems.

Table 21 - Detailed Performance Metrics for Resolution 2

Performance Metric	$M_{Process} - M_{Transportation}$	half-length	Confidence Interval
Avg. % Availability	-0.0176	0.0188	(-0.0363, 0.0012)
Avg. WT (days)	0.2611	0.1315	(0.1296, 0.3926)*
Avg. # Fixed at Base	-0.1750	0.5585	(-0.7335, 0.3835)
Base Avg. BO Age (days)	0.1088	0.3185	(-0.2098, 0.4273)
Avg. # Fixed at Depot	-0.2625	0.6761	(-0.9386, 0.4136)

* Represents statistically significant difference at 95%

Since the values in Table 21 are averages of the entire two year simulation run, we review monthly averages for percent availability and wait time over the two years. Figure 15 shows a drop in percent availability in month 5 for the process disruption. There is a two month recovery period after the disruption occurs, as depicted in month six. Although the actual difference in the decreased availability is only about 0.01%,

further investigation should be performed to determine what is actually happening during this drop. Similar results occur in Figure 16 for monthly average wait time, but there is a one month lag before seeing an impact from the process disruption in month five. Again, further investigation should be performed. Thus, we used a higher resolution model to gain more insight to impact from the disruptions.

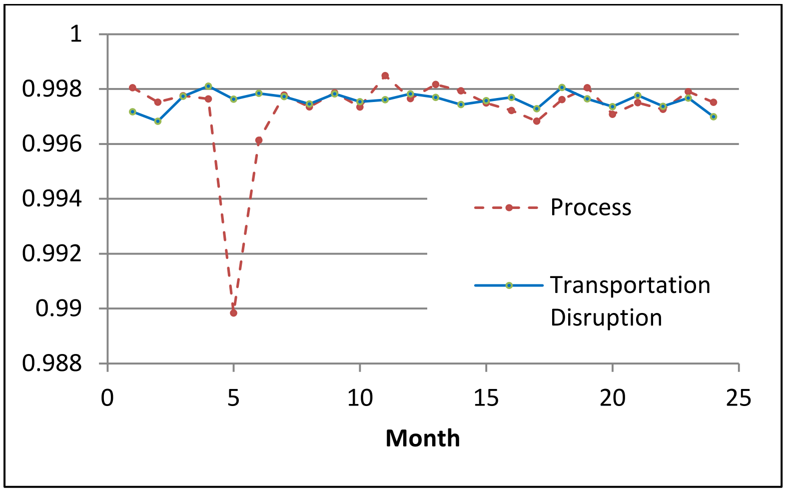


Figure 15- Monthly Average % Availability for Resolution 2

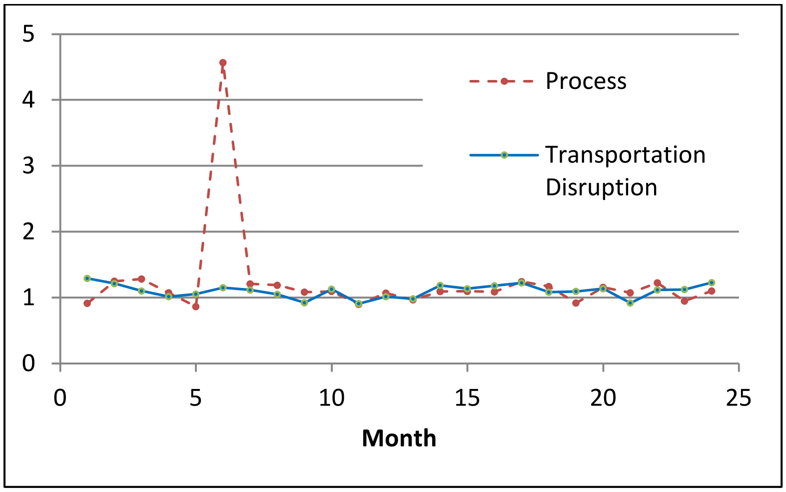


Figure 16 - Monthly Average Wait Time (days) for Resolution 2

Table 22 displays the difference in means, with 95% confidence intervals, between process disruption output and transportation disruption output for the resolution-three simulation. The performance metrics from this table are averages over the two year period simulated. As highlighted in the table, statistically significant difference between the two scenarios is apparent in average number of parts fixed at a base, time average number of backorders at a base, average number of backorders at a base, average number of backorders filled at a base, and total number of backorders at all bases. It should be noted that although there is statistical significance for time average number of backorders at a base, there is likely little practical significance because both averages are less than half a day with narrow confidence intervals.

Since Table 22 reports averages for the entire two year period, no insight can be gained for supply chain performance and risk throughout the two years. Therefore, monthly averages were again analyzed for percent availability and wait time.

Table 22 - Detailed Performance Metrics for Resolution 3

Performance Metric	$M_{Process}$ - $M_{Transportation}$	Half-length	Confidence Interval
Avg. % Availability	0.3761	0.6845	(-0.3084, 1.0606)
Avg. WT (days)	0.0379	0.1773	(-0.1394, 0.2152)
Avg. # Fixed at Base	10.1500	5.9871	(4.1629, 16.1371)*
Base TAB	-0.1474	0.0841	(-0.2315, -0.0633)*
Base Avg. BO Age (days)	1.2401	1.4937	(-0.2535, 2.7338)
Avg. # BO at Base	-6.1750	1.9759	(-8.1509, -4.1991)*
Avg. # BO Filled at Base	-6.0000	1.9283	(-7.9283, -4.0717)*
Total # of BOs at Bases	-18.5250	5.9276	(-24.4526, -12.5974)*
Avg. # Fixed at Depot	8.0250	9.5578	(-1.5328, 17.5828)
Depot TAB	0.0163	0.2904	(-0.2741, 0.3067)
Depot Avg. BO Age (days)	1.1467	4.0017	(-2.8550, 5.1484)
Avg. # BO at Depot	0.5375	1.2859	(-0.7484, 1.8234)
Avg. # BO Filled at Depot	0.4875	1.3972	(-0.9097, 1.8847)
Total # of BOs at Depots	0.9750	2.7944	(-1.8194, 3.7694)

* Represents statistically significant difference at 95%

Figure 17 shows a drop in percent availability to 88.6% in month five for the process disruption, but little change in percent availability around month five for the transportation disruption. Similarly, Figure 18 shows that average wait time spikes to 6.7 days in month five for the process disruption, but remains steady for the transportation disruption. In contrast to the resolution-two results, there are no lag or recovery periods in the resolution-three results.

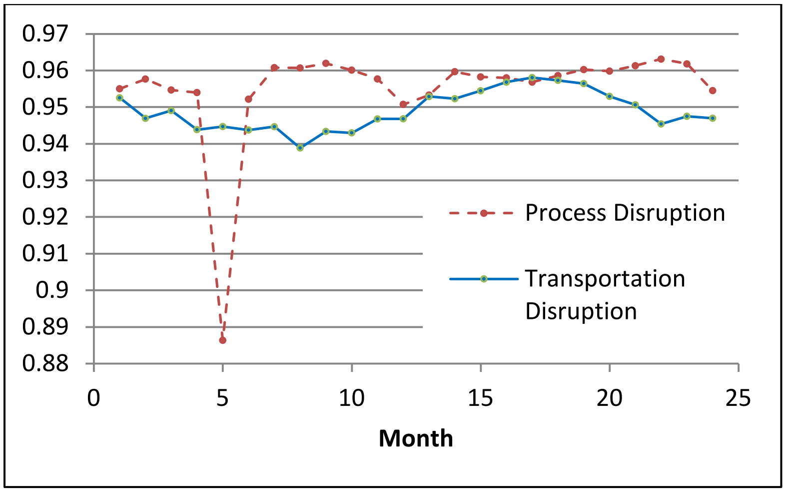


Figure 17 - Monthly Average % Availability for Resolution 3

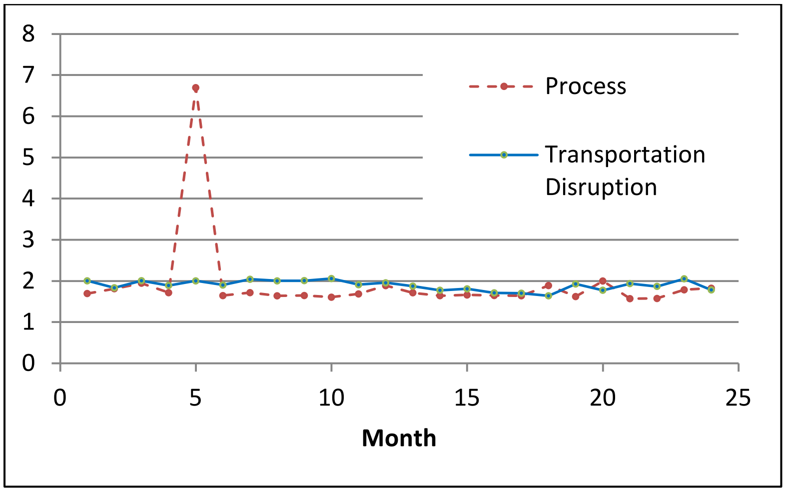


Figure 18 - Monthly Average Wait Time (days) for Resolution 3

6.8 Summary

This chapter demonstrated our modeling framework with the landing gear portion of the F-16 supply chain. It was shown that reduced funding for aircraft availability can significantly affect various risk metrics when the supply chain suffers from disruption events. Also, it was determined that monthly average metrics were required to detect the significant impact from disruptions modeled. Furthermore, multiple aggregation models were shown to significantly impact the usefulness of agent based variable resolution modeling.

7 Conclusion

This chapter summarizes contributions made to the field of Simulation presented in this document. It also provides areas for future study related to the research presented in this document.

7.1 Research Contributions

Our research develops a simulation framework for supply chain risk management, with focus on reparable items as shown in Figure 19. By integrating data mining software agents, variable resolution agent based modeling and simulation, and reparable item

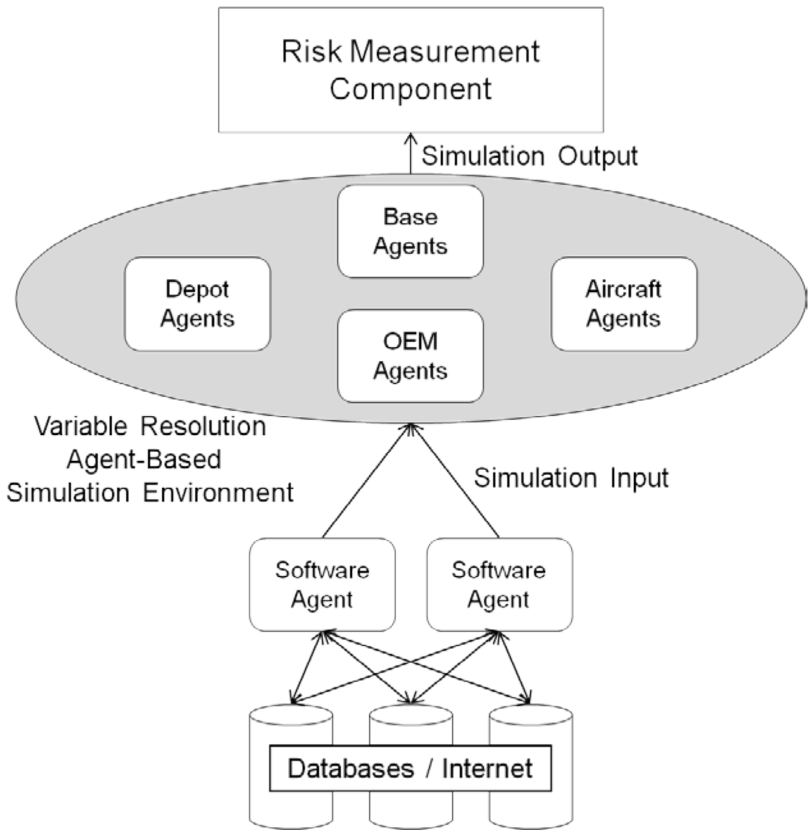


Figure 19 - Supply Chain Modeling and Analysis Framework

risk metrics we have developed a dynamic, intelligent, integrated, responsive, reactive, cooperative, interactive, and adaptable modeling framework that can sufficiently model risk of large supply chains. The modeling framework can be used to assess potential risks, risk mitigation strategies, or periodically track supply chain performance over time to determine susceptibility to risks.

Software Agents have been extensively used for data mining, but have not been dynamically integrated with agent based simulation agents. Existing work uses software agents to simulate on a small scale the interactive agents of the real system. This requires extensive coding and programming platform development. Our framework utilizes simulation software to develop the simulated entities and environment. This method takes advantage of the thoroughly developed modeling environment, which already contains functions and logic to enhance models. For example, most simulation software has built in statistics blocks, plots, message passing, queuing logic, etc.

Variable resolution modeling has a strong background in discrete event simulation, but has not been applied to agent based modeling and simulation (ABMS). We extend the lookup table and hierarchical concepts of variable resolution to ABMS, and provide further guidelines for aggregation and disaggregation of supply chain models.

Supply chain risk metrics described in literature focus on consumable item supply chains. Reparable item supply chains generally have greater complexity, for which additional metrics are needed to analyze performance and risk. We present new metrics, along with existing metrics, in a framework for reparable item supply chain management. New metrics include time average number of backorders and ratio of an item's inventory

cost to its size. The former metric provides insight to average number of backorders at any point in time over a span of time, while the latter metric provides insight for inventory management. Furthermore, we discuss aggregation and disaggregation of metrics.

Application of our framework to the landing gear portion of the F-16 supply chain demonstrated the modeling capability for a large and complex global supply chain. Analysis of process disruptions at the base level proved to cause more impact on the overall supply chain performance than transportation disruptions between the bases and depots. Including the time average number of backorders proved to enable greater insight of supply performance. However, this metric cannot stand by itself, because it contains no information about duration the backorders remain unfilled.

The overall contribution is a well defined and flexible supply chain risk management framework, which is divided into three smaller contributions:

- Integration of software agents with agent based modeling and simulation (ABMS) agents
    - software agents performing data mining to produce inputs for agent based simulation
- ABMS guidelines for aggregation / disaggregation of supply chain agents and interactions
    - Designing agent structure to allow for easy scalability in terms of fidelity
- Supply chain risk metrics framework for reparable item supply chains
    - Selectable and scalable in terms of fidelity

7.2 Advantages and Disadvantages

A primary advantage of the presented modeling framework is that it provides a powerful and flexible methodology for modeling and simulation. The framework combines software agents and agent based modeling and simulation, both of which have a great deal of existing research and technological advances.

Because the model is powerful and flexible it could be difficult to scope the model and define levels of resolution. Furthermore, no single metrics framework is adequate for every supply chain. This implies a large amount of work and planning must be put into sculpting the generic reparable item risk measurement framework to each supply chain.

7.3 Future Research

An area of particular interest for future study is enhancement to the variable resolution agent based simulation via agent logic to respond to disruptions. By expanding into intelligent agent technology more applicable analysis can be conducted to help decision makers determine how to manage their personnel and other supply chain entities. Another area of interest is variance reduction techniques for agent based modeling and simulation. The ability to incorporate variance reduction in variable resolution ABMS could prove to be difficult.

With the application model, there are several areas for enhancement and further analysis. One question of interest is ‘what can be done to reduce total non mission capable time due to supply without more money being allotted?’ Another area of interest is analyzing the risk of changing war time location of warehouse, suppliers, and

maintainers. Lastly, analysis of critical versus non-critical parts to make aircraft non-mission capable could provide great insight to supply chain risk management for the Air Force.

Bibliography

Adhitya, A., R. Srinivasan and I.A. Karimi. 2009. “Supply Chain Risk Identification Using a HAZOP-Based Approach,” AIChE Journal 55(6), 1447-1463.

AFGLSC (Air Force Global Logistics Support Center). 2011. Presentation. Supply Chain Optimization through Risk and Predictive Analytics for Decision Support (SCORPAD).

AFMC (Air Force Materiel Command). 2003. AFMC Metrics Guide. Wright-patterson AFB: HQ AFMC.

AFMC (Air Force Materiel Command). 2005. AFMC Guide to Supply Chain Management V9.0. Wright-patterson AFB: HQ AFMC.

Agentland. 2010. Intelligent agents. Available via www.agentland.com [Retrieved October 5, 2010].

Ahmed, S., U. Cakmak and A. Shapiro. 2007. “Coherent risk measures in inventory problems,” European Journal of Operational Research 182(1), 226-238.

Amouzegar, M.A., R.S. Tripp, R.G. McGarvey, M.J. Neumann, D. George, and J. Cornuet. 2008. “Sense and Respond Combat Support: Command and Control-Based Approach,” Air Force Journal of Logistics 31(4), 3-15.

Axe, D. 2010. “Lockheed Cross-Breeding Raptors, Joint Strike Fighters,” Wired Magazine. http://www.wired.com/dangerroom/2010/12/lockheed-cross-breeding-raptors-joint-strike-fighters/ [Retrieved May 10, 2011].

Axtell, R. L. 1992. Theory of Model Aggregation for Dynamical Systems with Application to Problems of Global Change. Dissertation: Carnegie-Mellon University.

Balci, O. 1997. “Verification, Validation and Accreditation of Simulation Models,” In Proceedings of the 1997 Winter Simulation Conference, ed. S. Andradottir, K. J. Healy, D. H. Withers, and B. L. Nelson, 135-141. Atlanta, GA: Institute of Electronics Engineers, Inc.

Balestreri, W. G. and P. S. McDoniel. 2002. Measuring Success: Metrics that Link Supply Chain Management to Aircraft Readiness. Thesis: Naval Postgraduate School.

Barbaro, A. F. and M. Bagajewicz. 2004. “Managing financial risk in planning under uncertainty,” AIChE J. 50, 963-989.

Bargbarosoglu, G. and T. Yazgac. 2000. “A decision support model for customer value assessment and supply quota allocation,” Production Planning & Control 11(6), 608–616.

BBN Technologies. 2004. “Cougaar Architecture Document,” Available via http://cougaar.org/twiki/pub/Main/CougaarDocuments/CAD_11_4.pdf [Retrieved September 16, 2010].

Bhagwat, R. and M. K. Sharma. 2007. “Performance measurement of supply chain management: A balanced scorecard approach,” Computers & Industrial Engineering 53, 43-62.

Bogataj, D. and M. Bogataj. 2007. “Measuring the supply chain risk and vulnerability in frequency space,” International Journal of Production Economics 108(1/2), 291-301.

Brewer, P.C and T.W. Speh. 2000. “Using the Balanced Scorecard to Measure Supply Chain Performance,” Journal of Business Logistics 21(1), 75-93.

Brown, N. 2010. “Model Flexibility: Development of a Generic Data-Driven Simulation,” In Proceedings of the 2010 Winter Simulation Conference, ed. B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yucesan, 1366-1375. Baltimore, MD: Institute of Electronics Engineers, Inc.

Bui, T. and J. Lee. 1999. “An agent-based framework for building decision support systems,” Decision Support Systems 25(3), 225-237.

Cao, H., F. Cheng, H. Xi, M. Ettl, S. Buckly, and C. Rodriguez. 2003. “A Simulation-Based Tool for Inventory Analysis in a Server Computer Manufacturing Environment,” In Proceedings of the 2003 Winter Simulation Conference. New Orleans, LA. 7-10 December 2003, 1313-1318.

Caridi, M., R. Cigolini and D. De Marco. 2005. “Improving supply-chain collaboration by linking intelligent agents to CPFR,” International Journal of Production Research 43(20), 4191-4218.

Caridi, M., L. Crippa, A. Perego, A. Sianesi and A. Tumino. 2010. “Measuring visibility to improve supply chain performance: a quantitative approach,” Benchmarking: An International Journal 17(4), 593-615.

Carrico, T. and M. Greaves. 2008. "Agent Applications in Defense Logistics," Defense Industry Applications of Autonomous Agents and Multi-Agents Systems, Whitestain Series in Software Agent Technologies and Automatic Computing, 51-72.

Chan, F.T.S. and H.J. Qi. 2003. "Feasibility of performance measurement system for supply chain: a process-based approach and measures," Integrated Manufacturing Systems 14(3), 179-190.

Chaturvedi, A., J. Chi, S. Mehta, and D. Dolk. 2004. "SAMAS: Scalable Architecture for Multi-resolution Agent-Based Simulation," Lecture Notes in Computer Science 3038: 779-788.

Chen, S.H. and Y.C. Huang. 2007. "Relative risk aversion and wealth dynamics," Information Sciences 177(5), 1222-1229.

Chen, D., Z. Zhou, and R. Hu. 2008. "Research on the inventory scheduling model based on agent-oriented Petri net in supply chain," Kybernetes 37(9/10), 1234-1241.

Choi, T.M., D. Li, H. Yan and C.H. Chiu. 2008. "Channel coordination in supply chains with agents having mean-variance objectives," Omega 36(4), 565-576.

Chopra, S. and M.S. Sodhi. 2004. "Managing risk to avoid supply-chain breakdown," Sloan Management Review 46(1), 53-61.

Christopher, M. and H. Peck. 2004. "Building the resilient supply chain," International Journal of Logistics Management 15(2), 1-13.

Craighead, C.W., J. Blackhurst, M.J. Rungtusanatham and R.B. Handfield. 2007. "The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities," Decision Sciences 38(1), 131-156.

Croft, D. 2004. Intelligent Software Agents: Definitions and Applications. Available via http://alumnus.caltech.edu/~croft/research/agent/definition/ [Retrieved October 21, 2010].

Cucchiella, F. and M. Gastaldi. 2006. "Risk management in supply chain: a real option approach," Journal of Manufacturing Technology Management 17(6), 700-720.

Datta, P.P, M. Christopher and P. Allen. 2007. "Agent-based modeling of complex production/distribution systems to improve resilience," International Journal of Logistics: Research and Applications 10(3), 187-203.

Da Silva, J.C., M. Klusch, S. Lodi and G. Moro. 2006. “Privacy-preserving agent-based distributed data clustering,” Web Intelligence and Agent Systems: An International Journal 4(2), 221-238.

Davis, P. 1993. An Introduction to Variable-Resolution Modeling and Cross-Resolution Model Connection. RAND R-4252-DARPA, Santa Monica, CA.

Davis, P. and R. Hillestad. 1993. “Families of Models that Cross Levels of Resolution: Issues for Design, Calibration and Management,” In Proceedings of the 1993 Winter Simulation Conference, ed. G. W. Evans, M. Mollaghasemi, E. C. Russell, and W. E. Biles, 1003-1012. Los Angeles, CA: Institute of Electronics Engineers, Inc.

Davis, P. and R. Huber. 1992. Variable-Resolution Combat Modeling: Motivations, Issues, and Principles. RAND N-3400-DARPA, Santa Monica, CA.

Department of Defense (DoD). 1995. Department of Defense Modeling and Simulation Master Plan. DoD Directive 5000.59-P. Washington: GPO, 1995.

Department of Defense (DoD). 2004. Presentation. DoD Logistics Balanced Scorecard Overview. 27 May 2004.

Ellis, S.C., R.M. Henry and J. Shockley. 2010. “Buyer perceptions of supply disruption risk: A behavioral view and empirical assessment,” Journal of Operations Management 28(1), 34-46.

Faisal, M.N., D.K. Banwet and R. Shankar. 2006. “Supply chain risk mitigation: modeling the enablers,” Business Process Management Journal 12(4), 535-552.

Farris, M.T. and P.D. Hutchison. 2002. “Cash-to-cash: the new supply chain management metric,” International Journal of Physical Distribution & Logistics Management 32(4), 288-298.

Foroughi, A., M. Albin and M. Kocakulah. 2006. “Perspectives on Global Supply Chain Supply-Side Risk Management,” In proceedings of the 2006 PICMET Conference on Technology Management for the Global Future. Istanbul, Turkey. 8-13 July 2006, 2732-2740.

Fox, M.S., M. Barbuceanu and R. Teigen. 2000. “Agent-Oriented Supply-Chain Management,” International Journal of Flexible Manufacturing Systems 12(2-3), 165-188.

Fox, M., J. Chionglo and M. Barbuceanu. 1993. “The integrated supply chain management system,” Available via www.eil.utoronto.ca/iscm-descr.html [accessed 20 November 2010].

Frey, D., T. Stockheim, P.O. Woelk and R. Zimmermann. 2003. "Integrated Multi-agent-based Supply Chain Management," In Proceedings of the 12th IEEE International Workshops on Enabling Technologies: Infrastructure for Collaborative Enterprises. Linz, Austria. 9-11 June 2003, 24-29.

Frost, B. 2000. Measuring Performance: Using the New Metrics to Deploy Strategy and Improve Performance. Measurement International: Dallas, TX.

Garcia-Flores, R., X.Z. Wang and G.E. Goltz. 2000. "Agent-based information flow for process industries' supply chain modeling," Computers and Chemical Engineering 24(2-7), 1135-1141.

Gaur, S. And A.R. Ravindran. 2006. "A bi-criteria model for the inventory aggregation problem under risk pooling," Computers & Industrial Engineering 51(3), 482–501.

Ghoshal, S. 1987. "Global strategy: an organizing framework," Strategic Management Journal 8(5), 425-40.

Gilbert, N. 2007. Agent Based Models. Sage Publications, Inc.: Thousand Oaks, California.

Globalsecurity.org. 2011. F-22 Raptor Pictures. http://www.globalsecurity.org/military/systems/aircraft/f-22-pics.htm. [Retrieved April 14, 2010].

Globerson, S. 1985. "Issues in developing a performance criteria system for an organization," International Journal of Production Research 23(4), 639–646.

Goh, M., J.Y.S. Lim and F. Meng. 2007. "A stochastic model for risk management in global supply chain networks," European Journal of Operational Research 182(1), 164-73.

Gunasekaran, A. and B. Kobu. 2007. "Performance measures and metrics in logistics and supply chain management: a review of recent literature (1995-2004) for research and applications," International Journal of Production Research 45(12), 2819-2840.

Gunasekaran, A., C. Patel and E. Tirtiroglu. 2001. "Performance measures and metrics in a supply chain environment," International Journal of Operations & Production Management 21(1/2), 71-87.

Harper, T.J. 2010. Agent Based Modeling and Simulation for Supply Chain Inventory Control. Unpublished manuscript, Air Force Institute of Technology, Wright Patterson Air Force Base, OH.

Hausman, W.H., H.L. Lee and U. Subramanian. 2005. Global Logistics Indicators, Supply Chain Metrics, and Bilateral Trade Patterns. World Bank Policy Research Working Paper No. 3773. Available via http://ssrn.com/ abstract=869999 [Retrieved October 20, 2010].

Heath, B. 2010. The History, Philosophy and Current Practice of Agent-Based Modeling and the Development of the Conceptual Model for Simulation Diagram. Dissertation: Wright State University.

Heilprin, J. 2012. "U.S. vows to protect supply chains," Dayton Daily News 26 January 2012: A4. Print.

Helsinger, A., M. Thome and T. Wright. 2005. "Cougaar: A Scalable, Distributed Multi-Agent Architecture," In Proceedings of Systems, Man and Cybernetics, 2004 IEEE International Conference. The Hague, The Netherlands. 10-13 October 2004, 1910-1917.

Houshyar, A.N., M. Mukhtar and R. Sulaiman. 2010. "Simulating the effect of Supply Chain Risk and Disruption: "A Malaysian Case Study"," In Proceedings of the 2010 International Symposium in Information Technology. Kuala Lumpur, Malaysia. 15-17 June 2010, 1362-1367.

Hunter, L.M., C.J. Kasouf, K.G. Celuch and K.A. Curry. 2004. "A classification of business-to- business buying decisions: risk importance and probability as a framework for e-business benefits," Industrial Marketing Management 33(2), 145–154.

Ito, T. and S.M.M.J. Abadi. 2002. "Agent-based material handling and inventory planning in warehouse," Journal of Intelligent Manufacturing 13(3), 201-210.

JDMAG (Joint Depot Maintenance Activities Group). 2010. Joint Service Best Business Practices. Available via http://www.jdmag.wpafb.af.mil/bestbusairforce.htm [Retrieved November 23, 2010].

Jedermann, R., C. Behrens, D. Westphal and W. Lang. 2006. "Applying autonomous sensor systems in logistics – Combining sensor networks, RFIDs and software agents," Sensors and Actuators A: Physical 132(1), 370-375.

Jiang, C. and Z. Sheng. 2009. "Case-based reinforcement learning for dynamic inventory control in a multi-agent supply-chain system," Expert Systems with Applications 36(3), 6520-6526.

Jirong, W., L. Jun, Z. Yunhong, and H. Zongwu. 2008. "Simulation Study on Influences of Information Sharing to Supply Chain Inventory System Based on Multi-agent System," In Proceedings of IEEE International Conference on Automation and Logistics. Qingdao, China. 1-3 September 2008, 1001-1004.

Jorion, P. 2002. "How Informative Are Value-at-Risk Disclosures?"The Accounting Review 77(4), 911-931.

Julka, N., R. Srinivasan and I. Karimi. 2002. "Agent-based supply chain management – 1: framework," Computers and Chemical Engineering 26(12), 1755-1769.

Juttner, U., H. Peck and M. Christopher. 2003. "Supply Chain Risk Management: Outlining an Agenda for Future Research," International Journal of Logistics: Research & Applications 6(4), 197-210.

Kaplan, R. and D.P. Norton. 1992. "The Balanced Scorecard – Measures that Drive Performance." Harvard Business Review 70, 71-79.

Khan, O. and B. Burnes. 2007. "Risk and supply chain management: creating a research agenda," International Journal of Logistics Management 18(2), 197-216.

Kirkwood, C.W., M.P. Slaven and A. Maltz. 2005. "Improving supply-chain reconfiguration decisions at IBM," Interfaces 35(6), 460–473.

Kleindorfer, P.R. and L.K. Wassenhove. 2004. Managing risk in global supply chains. The INSEAD-Wharton Alliance on Globalizing. Cambridge University Press, 288-305.

Kleijnen, J.P.C. and M.T. Smits. 2003. "Performance metrics in supply chain management," Journal of the Operational Research Society 54(1), 507-514.

Krishnamurthy, P., F. Khorrami, and D. Schoenwald. 2008. "Decentralized Inventory Control for Large-Scale Reverse Supply Chains: A Computationally Tractable Approach," IEEE Transactions on systems, man, and cybernetics 38(4), 551-561.

Kroger, W. 2008. "Critical infrastructure at risk: A need for a new conceptual approach and extended analytical tools," Reliability Engineering and System Safety 93(12), 1781-1787.

Kull, T. and D. Closs. 2008. "The risk of second-tier supplier failures in serial supply chains: Implications for order policies and distributor anatomy," European Journal of Operational Science 186(3), 1158-1174.

Kull, T.J. and S. Talluri. 2008. “A Supply Risk Reduction Model Using Integrated Multicriteria Decision Making,” IEEE Transactions on Engineering Management 55(3), 409-419.

Leemis, L. M. 2004. “Building Credible Input Models,” In Proceedings of the 2004 Winter Simulation Conference, ed. R. G. Ingalls, M. D. Rossetti, J. S. Smith, and B. A. Peters, 29-40. Washington, DC: Institute of Electronics Engineers, Inc.

Leonard, M. 2004. Air Force Materiel Command: A Survey of Performance Measures. Thesis: Air Force Institute of Technology.

Li, X. and C. Chandra. 2007. “A knowledge integration framework for complex network Management,” Industrial Management & Data Systems 107(8), 1089-109.

Li, W., and C. Li. 2008. “Transshipment Policy Research of Multi-Location Inventory System Based on Multi-Agent System,” In Proceedings of IEEE International Conference on Automation and Logistics. Qingdao, China. 1-3 September 2008, 1344-1351.

Li Y., L. Wang and M.A. Heyde. 2010. “Risk Assessment of Supply Chain System Based on Information Entropy,” In Proceedings of the 2010 International Conference on Logistics Systems and Intelligent Management. Harbin, China. 9-10 January 2010, 1566-1568.

Li, Y. and L. Zhao. 2009. “Supply Chain Risk Measurement and Transmission Based on Products Pricing,” In Proceeding of the 2009 International Joint Conference on computational Sciences and Optimization. Sanya, Hainan. 24-26 April 2009, 328-332.

Lockheed Martin. 2011. Lockheed Martin F-22 Raptor diagram. http://www.aerospaceweb.org/ aircraft/fighter/f22/pics06.shtml [Retrieved June1, 2011].

Macal, C. M. and M. J. North. 2005. “Tutorial on Agent-Based Modeling and Simulation,” In Proceedings of the 2005 Winter Simulation Conference, ed. M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 2-15. Orlando, FL: Institute of Electronics Engineers, Inc.

Macal, C. M. and M. J. North. 2006. “Tutorial on Agent-Based Modeling and Simulation Part 2: How To Model With Agents,” In Proceedings of the 2006 Winter Simulation Conference, ed. L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, and R. M. Fujimoto, 73-83. Monterey, CA: Institute of Electronics Engineers, Inc.

Manuj, I. and J.T. Mentzer. 2008. "Global supply chain risk management strategies," International Journal of Physical Distribution & Logistics Management 38(3), 192-223.

Maskell, B. 1989. "Performance measures of world class manufacturing," Management Accounting 67, 32–33.

Mason-Jones, R., B. Naylor and D.R. Towell. 2000. "Engineering the leagile supply chain," International Journal of Agile Management Systems 2(1), 54-61.

Min, H. and G. Zhou. 2002. "Supply chain modeling: past, present and future," Computers & Industrial Engineering 43(1-2), 231-249.

Moyaux, T., B. Chaib-draa and S. D'Amours. 2006. Multiagent-Based Supply Chain Management. Springer: Berlin Heidelberg, 1-27.

Naraharisetti, P.K., A. Adhitya, I.A. Karimi and R. Srinivasan. 2009. "From PSE to PSE^2 – Decision support for resilient enterprises," Computers and Chemical engineering 33(12), 1939-1949.

Neely, A.D., M.J. Gregory and K.W. Platts. 1995. "Performance measurement system design: a literature review and research agenda," International Journal of Operations & Production Management 15(4), 80–116.

Neiger, D., K. Rotaru and L. Churilov. 2009. "Supply chain risk identification with value-focused process engineering," Journal of Operations Management 27(2), 154-168.

Neureuther, B.N.D. and G. Kenyon. 2009. "Mitigating supply chain vulnerability," Journal of Marketing Channels 16(3), 245-263.

Nienaber, R.C. and A. Barnard. 2007. "A Generic Agent Framework to Support the Various Software Project Management Processes," Interdisciplinary Journal of Information, Knowledge, and Management 2, 149-162.

Nikolai, C. and G. Madey. 2009. "Tools of the Trade: A Survey of Various Agent Based Modeling Platforms," Journal of Artificial Societies and Social Simulation 12(2), 1-2.

North, M.J. and C.M. Macal. 2007a. Managing business complexity: discovering strategic solutions with agent-based modeling and simulation. Oxford University Press, Inc.: Oxford, NY.

North, M. J. and C. M. Macal. 2007b. "Tutorial on Agent-based Modeling and Simulation," 75th Military Operations Research Society Symposium (MORSS). Annapolis, MD.

Nwana, H.S. 1996. "Software Agents: An Overview," Knowledge Engineering Review 11(3), 205-244.

Oluwole, T.A. 2008. The Role of Software Agents in Supply Chain Risk Management Related to the Procurement Process in the Aerospace Manufacturing Industry. Capstone Report.

Othman, Z.A., A.A. Bakar, A.R. Hamdan, K. Omar and N.L.M. Shuib. 2007. "Agent Based Preprocessing," In Proceedings of the International Conference on Intelligent and Advanced Systems. Kuala Lumpur, Malaysia. 25-28 November 2007, 219-223.

PACAF. 2011. Pacific Air Forces. http://www.pacaf.af.mil/photos/media_search.asp?q=f-22%20f-22s%20f-22a&page=6 [Retrieved June 5, 2011].

Pai, W.C., C.C. Wang, and D.R. Jiang. 2000. "A software development model based on quality measurement," In Proceedings of the ICSA 13th International Conference, Computer Applications in Industry and Engineering. Honolulu, HI. 1-3 November 2000, 40-43.

Pai, R.R., V.R. Kallenpalli, R.J Caudill and M. Zhou. 2003. "Methods Toward Supply Chain Risk analysis," In Proceedings of the 2003 IEEE International Conference on Systems, Man and Cybernetics. 5-8 October 2003, 4560-4565.

Pan, A., S.Y.S. Leung, K.L. Moon, and K.W. Yeung. 2009. "Optimal reorder decision-making in the agent-based apparel supply chain," Expert Systems with Applications 36(4), 8571-8581.

Parker, C. 2000. "Performance measurement," Work Study 49(2), 63–66.

Pawlaszczyk, D. and S. Strassburger. 2009. "Scalability in Distributed Simulations of Agent-Based Models," In Proceedings of the 2009 Winter Simulation Conference, ed. M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin and R. G. Ingalls, 1189-1200. Austin, Texas: Institute of Electrical and Electronics Engineers, Inc.

Pettit, T.J., J. Fiksel and K.L. Croxton. 2010. "Ensuring Supply Chain Resilience: Development of a Conceptual Framework," Journal of Business Logistics 31(1), 1-21.

Pham, V.A. and A. Karmouch. 1998. “Mobile Software Agents: An Overview,” IEEE Communications Magazine 36(7), 26-37.

Ponomarov, S.Y. and M.C. Holcomb. 2009. “Understanding the concept of supply chain resilience,” International Journal of Logistics Management 20(1), 124-143.

Poojari, C.A., C. Lucas and G. Mitra. 2008. “Robust solutions and risk measures for a supply chain planning problem under uncertainty,” Journal of Operational Research Society 59(1), 2-12.

Qiang, B. and G. Jingjuan. 2010. “Evaluation model of supply chain risk based on principle component analysis,” In Proceedings of the 2010 International Conference on Logistics Systems and Intelligent Management. Harbin, China. 9-10 Jan. 2010, 1436-1440.

Rabelo, L., H. Eskandari, T. Shaalan and M. Helal. 2007. “Value chain analysis using hybrid simulation and AHP,” International Journal of Production Economics 105(2), 536–547.

Rana, O. F. and K. Stout. 2000. “What is Scalability in Multi-Agent Systems,” In Proceedings of the fourth International Conference on Autonomous Agents, 56-63.

Reese, A., 2007. Enabling supplier enablement at oracle. Supply & Demand Chain. Available via http://www.sdcexec.com/print/Supply-and-Demand-Chain-Executive/Enabling-Supplier-Enablement-at-Oracle/1$9275 [Retrieved October 20, 2010].

Rice, J.B. and F. Caniato. 2003. “Building a secure and resilient supply network,” Supply Chain Management Review **7**(5), 22–30.

Ritchie, B. and C. Brindley. 2007. “Supply chain risk management and performance,” International Journal of Operations & Production Management 27(3), 303-322.

Rodriguez, J. F. D. 2008. Metamodeling Techniques to Aid in the Aggregation Process of Large Hierarchical Simulation Models. Dissertation: Air Force Institute of Technology.

Sabio, N., M. Gadalla, G. Guillen-Gosalbez and L. Jimenez. 2010. “Strategic planning with risk control of hydrogen supply chains for vehicle use under uncertainty in operating costs: A case study of Spain,” International Journal of Hydrogen Energy 35(13), 6836-6852.

Sanchez-Rodriguez Vasco, Andrew Potter and Mohamed M. Naim. 2010. “Evaluating the causes of uncertainty in logistics operations,” International Journal of Logistics Management 21(1), 45-64.

Schmitt, A.J. and M. Singh. 2009. “Quantifying Supply Chain Risk Using Monte Carlo and Discrete-Event Simulation,” In Proceedings of the 2009 Winter Simulation Conference. Austin, TX. 13-16 December 2009, 1237-1248.

Shi, D. 2004. “A Review of Enterprise Supply Chain Risk Management,” Journal of Systems Science and Systems Engineering 13(2), 219-244.

Si, Y.W. and S.F. Lou. 2009. “Fuzzy adaptive agent for supply chain management,” Web Intelligence and Agent Systems: An International Journal 7(2), 173-194.

Singh, S., C.D. McAllister, D. Rinks and X. Jiang. 2010. “Implication of risk adjusted discount rates on cycle stock and safety stock in a multi-period inventory model,” International Journal of Production Economics 123(1), 187-195.

Sink, D.S. and T.C. Tuttle. 1989. Planning and Measurement in Your Organization of the Future. Industrial Engineering and Management Press: Norcross, GA.

Sirivunnabood, S. and S. Kumara. 2009. “Comparison of Mitigation Strategies for Supplier Risks: a Multi Agent-Based Simulation Approach,” In Proceedings of IEEE/INFORMS International Conference on Service Operations, Logistics and Informatics. Chicago, IL. 22-24 July 2009, 388-393.

Snyder, L.V., M.S. Daskin and C.P. Teo. 2007. “The stochastic location model with risk pooling,” European Journal of Operational Research 179(3), 1221-1238.

Sokolova, M and A. Fernandez-Caballero. 2009. “Modeling and implementing an agent-based environmental health impact decision support system,” Expert Systems with Applications 36(2), 2603-2614.

Srinivas and J.A. Harding. 2008. “A data mining integrated architecture for shop floor control,” In Proceedings of the Institute of Mechanical Engineers, Part B: Journal of Engineering Manufacture 222(5), 605-624.

Svensson, G. 2000. “A conceptual framework for the analysis of vulnerability in supply chains,” International Journal of Physical Distribution & Logistics Management 30(9), 731-749.

Swaminathan, J. M., S. F. Smith and N. M. Sadeh. 1998. “Modelling supply chain dynamics: a multi-agent approach,” Decision Sciences 29(3), 607-632.

Symeonidis, A.L., D.D. Kehagias and P.A. Mitkas. 2003. "Intelligent policy recommendations on enterprise resource planning by the use of agent technology and data mining techniques," Expert Systems with Applications 25(4), 589-602.

Tang, C.S. 2006. "Perspectives in supply chain risk management," International Journal of Production Economics 103(2), 451-488.

Tang, C.X.H., H.C.W. Lau and G.T.S. Ho. 2008. "A conceptual fuzzy-genetic algorithm framework for assessing the potential risks in supply chain management," International Journal of Risk Assessment & Management 10(3), 263-71.

Thadakamalla, H.P., U.N. Raghavan, S. Kumara, and R. Albert. 2004. "Survivability of Multiagent-Based Supply Networks: A Topological Perspective," IEEE Intelligent Systems 19(5), 24-31.

Trkman, P. and K. McCormack. 2009. "Supply chain risk in turbulent environments – A conceptual model for managing supply chain network risk," International Journal of Production Economics 119(2), 247-258.

Tuncel, G. and G. Alpan. 2010. "Risk assessment and management for supply chain networks: A case study," Computers in Industry 61(3), 250-259.

Upal, M.A. and F. Fung. 2003. "Dynamic Plan Evaluation for Military Logistics," In Proceedings of the 7th International Conference on Artificial Intelligence and Soft Computing, ACTA Press, 87-92.

Wagner, S.M. and C. Bode. 2006. "An empirical investigation into supply chain vulnerability," Journal of Purchasing & Supply Management 12(6), 301-312.

Wagner, S.M. and N. Neshat. 2010. "Assessing the vulnerability of supply chains using graph theory," International Journal of Production Economics 126(1), 121-129.

Wang, J. and Y.F. Shu. 2007. "A possibilistic decision model for new product supply chain design," European Journal of Operational Research 177(2), 1044–1061.

White, D. 1995. "Application of systems thinking to risk management," Management Decision 33(10), 35-45.

Wilson, M.C. 2007. "The impact of transportation disruptions on supply chain performance," Transportation Research Part E: Logistics and Transportation Review 43(4), 295–320.

WPAFB. 2011. Wright Patterson Air Force Base. http://www.wpafbaf.mil/photos/ mediagallery.asp?galleryID=2600&?id=-1&page=1&count=48 [Retrieved May 30, 2011].

Wu, D.J. 2001. “Software agents for knowledge management: coordination in multi-agent supply chains and auctions,” Expert Systems with Applications 20(1), 51-64.

Wu, T., J. Blackhurst and V. Chidambaram. 2006. “A model for inbound supply risk analysis,” Computers in Industry 57(4), 350–365.

Wu, D. and D.L. Olson. 2008. “Supply chain risk, simulation, and vendor selection,” International Journal of Production Economics 114(2), 646-655.

Wu, L., Y. Zhu, X. Li, and J. Yuan. 2004. “Application of Multi-agent and Data Mining Techniques in Condition Assessment of Transformers,” International Conference on Power System Technology. Singapore. 21-24 November 2004, 823-827.

Xiang, L. 2008. “An Agent-based Architecture for Supply Chain Finance Cooperative Context-aware Distributed Data Mining Systems,” The Third International Conference on Internet and Web Applications and Services. Athens, Greece. 8-13 June 2008, 261-266.

Xiaohui, W., Z. Xiaobing, S. Shiji and W. Cheng. 2006. “Study on risk analysis of supply chain enterprises,” Journal of Systems Engineering and Electronics 17(4), 781-787.

Yan, H., B. Xu and C. Wang. 2008. “Study on the Optimization Measures of Reducing Supply Chain Cooperation Risks,” In Proceedings of the 2008 International Symposiums on Information Processing. 23-25 May 2008, 109-113.

Yang, B. and Y. Yang. 2010. “Postponement in supply chain risk management: a complexity perspective,” International Journal of Production Research 48(7), 1901-1912.

Yongsheng, L. and Z. Kun. 2009. “Study on Evaluation Index System for Supply Chain Risk,” In Proceedings of the 1st International Conference on Information Science and Engineering. Chennai, India. 28-30 December 2009, 4510-4513.

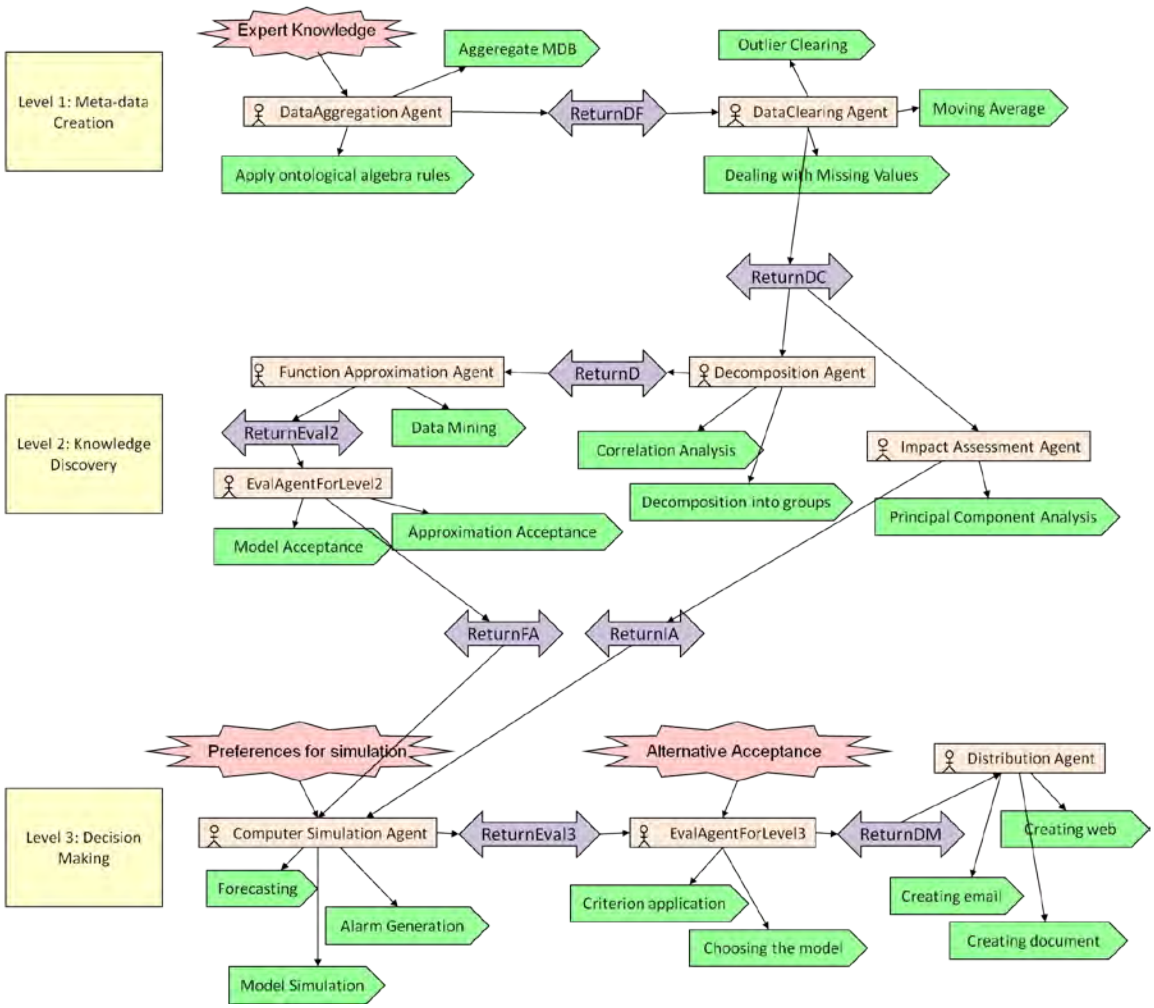
You, F., J.M. Wassick and I.E. Grossmann. 2009. “Risk Management for a Global Supply Chain Planning Under Uncertainty: Models and Algorithms,” AIChE Journal 55(4), 931-946.

Zeng, A. Z., P.D. Berger and A. Gerstenfeld. 2005. “Managing the supply-side risks in supply chains: taxonomies, processes and examples of decision-making modeling,” Applications of Supply Chain Management and E-Commerce Research. Springer, Berlin.

Zimmermann, R., S. Winkler and F. Bodendorf. 2006. “Agent-based Supply Chain Event Management – Concept and Assessment,” In Proceedings of the 39th Hawaii International Conference on System Sciences. Kauai, HI. 4-7 January 2006, 1-10.

Zongxue X., K. Jinno, A. Kawamura, S. Takesaki and K. Ito. 1998. “Performance Risk Analysis for Fukuoka Water Supply System,” Water Resources Management 12(1), 13-30.

Appendix A. Agent Decision Support System overview diagram (Sokolova and Fernandez-Caballero (2009)



Agent Based Modeling and Simulation Framework For Supply Chain Risk Management

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Introduction

Large supply chains continue to face ever increasing strain and risk, thus increasing the need for risk management tools. However, current supply chain risk management research focuses on consumable items. Therefore, this research will focus on repairable items to fill this research gap.

Comprised of software agents integrated with agent based simulation and supply chain risk metrics, the proposed framework can be used as a performance monitoring tool and to assess risk mitigation strategies. Software agents provide a natural means for data mining to develop simulation input, while agent based simulation software platforms provide an intuitive and rapid development method for simulating supply chains.

Motivation

- Large supply chains suffer from large complexity and scope (e.g. Millions of part types, interleaved organizations and processes, legacy databases, diminishing funding, globalization, etc.)
  - ➢Existing modeling techniques lack the dynamic, complexity and stochastic requirements necessary for modeling risk of large supply chains
  - ➢Software agents alone do not provide a natural and easily developable modeling technique
- Limited research exists for risk management of repairable item supply chains

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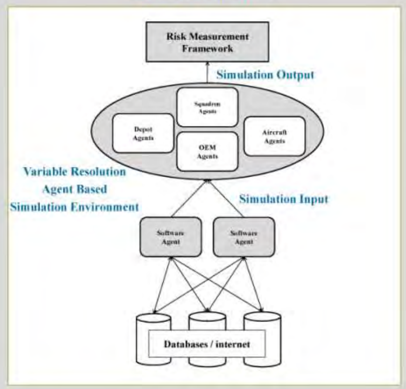
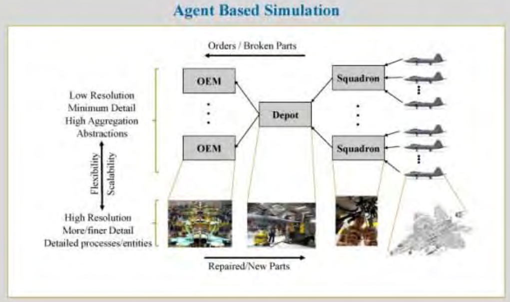
General Framework



Agent Based Simulation



Supply Chain Risks

- Port lockouts, terrorist attacks, natural disasters, information systems, transportation uncertainties, etc.

Risk Mitigation Strategies

- Postponement, hedging, flexible supply base, forecasting, redundancy, etc.

Risk Metrics

- Percentage of goods in transit, number of shared data sets, part-material size, etc.

Agent based Modeling and Simulation

- Ideal framework for exploring supply chain dynamics
  - ➢Bottom-up approach: define agent behaviors first
    - Enable interaction between agents
    - Allow complex behavior to emerge
  - ➢Enterprises in a supply chain (e.g. Manufacturer, wholesaler, etc.) have a natural translation to agents

Research Goals / Contributions

- Develop better supply chain risk management framework:
  - ➢Integrate software agents with an agent based simulation platform
  - ➢Develop agent design guidelines for easy scaling in levels of fidelity/aggregation
  - ➢Develop supply chain risk metrics framework for repairable item supply chains
- Demonstrate framework with Air Force aircraft supply chain (potentially F-22 or F-16)

Appendix C. Independent Study Report

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Agent Based Modeling and Simulation for Supply Chain Inventory Control

Independent Study Report

Tiffany Jill Harper

3/19/2010

Contents

1. Introduction

Jerong et al. state that “supply chain integrates supplier, manufacturer, wholesaler, retailer and end user to a system by logistics, business flow, information flow and cash flow (Jerong et al. 2008).” As depicted by Ito and Abadi, supply chain management attempts to enable “faster and more flexible coordination between a company and its customers and suppliers within the whole logistics chain (Ito and Abadi 2002).” Benefits resulting from successful supply chain management include improvements in forecasting accuracy of 25% to 80%, inventory reduction from 25% to 60%, inventory and shipping accuracy rates over 99%, and increased productivity from 20% to 30% (Ito and Abadi 2002).

Strategic, tactical, and operational are the three levels of decision-making in supply chain management (Pan et al. 2009). Strategic decisions are the long-term decisions involving location, production, inventory and transportation (Pan et al. 2009). Tactical decisions are medium-term decisions including production and materials requirement planning, weekly demand forecasting, and distribution and transportation planning (Pan et al. 2009). Operational decisions are short term decisions made daily (Pan et al. 2009).

Agent based modeling and simulation (ABMS) is a highly viable tool for augmenting these types of decisions throughout a supply chain. This paper focuses on ABMS for inventory control within the Air Force supply chain. The remainder of this paper presents background information on ABMS, ABMS for supply chain management, ABMS for inventory control, and presents an agent-based simulation model for inventory control.

2. Agent Based Modeling and Simulation

Agent-based modeling and simulation characterizes a system by allowing individual agents to perform a set of behavior rules, which leads to interactions between agents and between agents and their environment. This method of simulation is “founded on the notion that the whole of many systems or organizations is greater than the simple sum of their constituent parts (North and Macal 2007).” ABMS combines discrete-event simulation, which provides the interactions of individual components within a simulation, and object-oriented programming, which provides well-tested frameworks for organizing agents based on their behaviors (North and Macal 2007).

Agents are defined by Pan et al. as “active, persistent (software) components with the abilities of perceiving, reasoning, acting and communicating (Pan et al. 2009).” Having sets of attributes and behavior rules, agents are essentially the decision making components in complex adaptive systems (North and Macal 2007). While attributes describe the agent, the behavior rules dictate how agents respond to their environment and other agents, which leads to emergent behavior of the entire system.

ABMS originated from the study of complex adaptive systems and cellular automata, with some of the earliest agent-based models being “Game of Life” and sugarscape models (North and Macal 2007). For more details on the history of ABMS refer to (Heath 2010).

3. ABMS for Supply Chain

ABMS is highly germane to supply chain management because performance measures, such as productivity, shipping accuracy, and inventory can be predicted via a model prior to expending money and time on changing the actual system. Furthermore, enterprises in a supply chain (e.g. manufacturer, wholesaler, etc.) have a natural translation to agents. By adequately capturing the behavior rules of each enterprise, an agent-based model can be used to observe interactions between the enterprises and system performance can be derived from emergent system patterns.

According to Amouzegar et al. "agent-based models are already in wide use within the DoD for force-on-force simulations but have only recently been adapted for military logistics use (Amouzegar et al. 2008)." Some simple supply chain simulations for logistics have been done, but almost none have modeled actual organizations with sufficient detail to adequately compare alternative policies (Amouzegar et al. 2008). This is due to the complexity of the disparate, decentralized organizations that make up the Air Force supply chain. One initiative that demonstrates the utility of agents for military logistics is the Coalition Agent eXperiment (CoAX), led by the Defense Advanced Research Projects Agency (DARPA) (Amouzegar et al. 2008). From this initiative it became apparent that the following technological and social issues must be overcome for agents to effectively be implemented for military logistics planning:

- Technological issues: logistics business process modeling, protocols, ontologies, automated information-gathering, and security
- Social issues: trusting agents to do business for you, accountability and the law, humans and agents working together, efficiency metrics, ease of use, adjustable autonomy, adjustable visibility, and social acceptability versus optimality (Amouzegar et al. 2008)

DARPA has also been working on an end-to-end logistics model under the Advance Logistics Project, which was extended to the Ultra-log project (Amouzegar et al. 2008). As part of the Ultralog project, an agent-based model was developed to show how various supply-chain network topologies fare under attack (Thadakamalla et al. 2004). The model, built in Netlogo, was originally developed to analyze military supply chain vulnerability to terrorist or military attacks (Thadakamalla et al. 2004). Refer to the Netlogo website at http://jmvidal.cse.sc.edu/netlogomas/ for further details on this model.

For further information on ABMS for supply chains refer to (Jirong et al. 2008) and (Sirivunnabood and Kumara 2009), both of which provide brief literature reviews.

4. ABMS for Inventory Control

To provide a general overview of the applicability of ABMS specifically for inventory control, this section paraphrases several articles on ABMS relevant to inventory control. This section is not meant to be an exhaustive literature review, but rather provide several examples of recent research in the area of ABMS for inventory control.

> Ito and Abadi propose an agent-based model for a warehouse system composed of three subsystems; agent-based communication

system, agent-based material handling system, and agent-based inventory planning and control system. Warehouse systems take care of fluctuation and uncertainty of demands from customers, and provide just-in-time delivery of materials. That is because inventory avoids shortages, but at the cost of capital investment, operation and maintenance, material handling, and insurance. The model, written in Java, utilizes master agents and subagents including customer, supplier, order, inventory, product, supplier-order, and automatic-guided vehicle (AGV) agents. With further study proposed by the authors, the model will provide a mechanism for autonomous setting of parameters to determine the order points or order-up-to-level point of products based on the history of customer orders and supplier lead times. Furthermore, the model will provide a mechanism for effective job-allocation to AGVs and scheduling jobs of each AGV. (Ito and Abadi 2002)

Li and Li consider a multi-location inventory system with several retailers who share one supplier. The model, built using the Anylogic software, considers demand lead-time, replenishment lead-time, and transshipment lead-time. Also the model does not employ a central agency to decide transshipments, and retailers make their decisions separately. Running the model led to emergent transshipments happening between retailers when in-hand inventory and pipeline stock are not enough to meet the demand. Furthermore, optimal inventory policies were found by considering holding, ordering, transshipment, backorder, and transshipment benefit costs. (Li and Li 2008)

Chen, Zhou, and Hu propose an agent-oriented Petri net model for an inventory-scheduling model, with focus on the problems of analysis and modeling of multi-agent systems. Petri net aims at researching the organization structure and dynamic behavior of a system, with an eye on all the possible state changing and the relation of the change in the system. The proposed agent-oriented Petri net model is applied in modeling the inventory scheduling of supply system. (Chen et al. 2008)

Jirong et al. propose a 4-level multi-agent system model for supply chain inventory with a decision-making model for every node enterprise agent in the supply chain. This modeling technique was selected due to the dynamic nonlinear complexity of supply chain inventory systems. The simulation study is conducted for the influence of lead time and information sharing among the four agent types; retailer, wholesaler, distributor, and manufacturer. Results confirmed that the information sharing strategy effectively

decreases the variation amplitudes of inventory of each enterprise in the supply chain. That is, the bullwhip effect is diminished when enterprises in the supply chain share information. (Jirong et al. 2008)

Jiang and Sheng propose a reinforcement learning algorithm combined with case-base reasoning in a multi-agent supply-chain system. Reinforcement learning is an approach to machine intelligence that learns to achieve the given goal by trial-and-error iterations with its environment. This is done by combining dynamic programming and supervised learning. Recent research in this area tends to focus on mathematical or analytical models, such as Bayesian approach, Utility Function Method, fuzzy set concepts and autoregressive and Integrated Moving Average and Generalized Autoregressive Conditional Heteroscedasticity. The multi-agent simulation proposed in the article was programmed under Java2 Development Kit (JDK) 1.5 to study the problem of dynamic inventory control for satisfying target service level in supply chain with nonstationary customer demand. (Jiang and Sheng 2009)

Cao et al. describe a simulation-based inventory management tool developed for the IBM Enterprise Server Group. IBM's supply chain involves expensive components with high inventory carrying cost, extensive tests for components for high quality requirements, multi-tier suppliers with long lead time, and high customer service levels requiring complex product configuration and quick order response time. The fabrication stage is a build-to-plan process, while the fulfillment stage is a make-to-order process. Thus, the stages together form a hybrid process structure combined with inherent randomness in the process pose tremendous challenges to inventory management, particularly in terms of financial and operation impacts. To model impact of randomness in parameters like lead times, yields and component usage rates, the authors developed a simulation tool with Java. With inventory costs and Days-of-Supply profiles as outputs, the simulation tool provides decision support at an operational level. That is, the model provides the capability to project the future inventory performance for selected high-dollar parts in IBM Enterprise Server Manufacturing. (Cao et al. 2003)

Sirivunnabood and Kumara used an agent-based simulation model to determine appropriate risk mitigation strategies for a supply chain network under supplier risks. Implemented in Java on the Java Agent Development (JADE) platform, the model consists of

supplier agents, plant agents, warehouse agents, customer agents, and a controller agent. Unexpected events were randomly generated to mimic the risks that possibly occur in the supply chain. Having a redundant supplier and reserving more inventories were the two risk mitigation strategies tested for four types of risks, which were depicted by frequency and duration. (Sirivunnabood and Kumara 2009)

Krishnamurthy et al. consider a new inventory control technique for large-scale supply chains, which considers stochastic transport delays, manufacturing times, and repair times and probabilistic characterization of part repair success. Because stochastic disturbances enter at both ends of a bidirectional supply chain and the necessity for overly simplified assumption, optimization techniques for inventory control for bidirectional stochastic supply chains are computationally intractable. For this reason the paper provides an agent based simulation model of aircraft supply chain involving multiple original equipment manufacturers (OEMs), depots, bases, squadrons, and planes. ABMS was used to avoid explicitly modeling inventory dynamics for each sites and formulating complex coupling signals between the sites. With an adaptive feature, the model can adjust stock levels with the objective of reducing excess inventory and maintaining or increasing mission capability of aircraft. The simulation was written in Python language and ran 1000 days of simulation time in 25 minutes real time. Output from the model can be used to determine the number of parts of each part type that each site should order from its associated supplier site, and the number of parts of each part type to start manufacturing. (Krishnamurthy et al. 2008)

5. Example

5.1. Model

A simple supply chain model was built using Netlogo version 4.1. This model is based on the aircraft supply chain model presented by Krishnamurthy et al., in which aircraft parts fail, are sent upstream to be fixed or replaced by a new part, and then sent downstream to be installed on the aircraft, as depicted in **Figure 20**. Refer to Appendix A for a snapshot of the model interface from Netlogo.

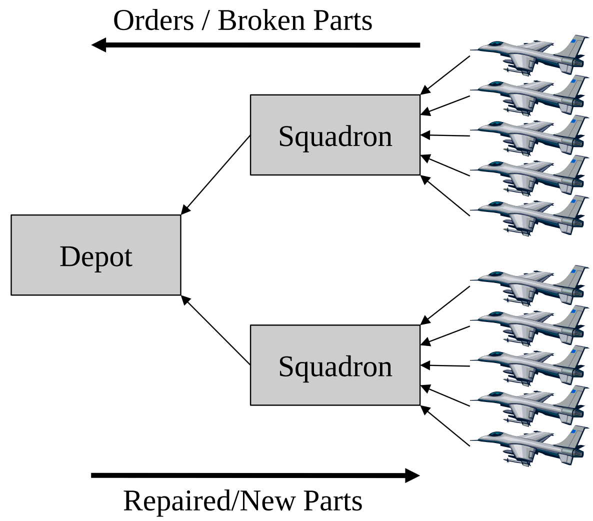


Figure 20 - Aircraft Supply Chain Flow

Model agents are planes, parts, squadrons, depots, and orders. Plane agents' main role is to track operating status of all the parts associated with that specific plane, thus tracking mission capability of the plane. Part Agents determine when that part will fail according to a statistical distribution, and tracks the time to repair the part. When a part fails it creates an order agent and sends this order agent to the squadron assigned to that plane. Order agents simulate the travel of broken parts upstream and fixed, or new, parts downstream. They arrive at a destination to be processed when their travel counter reaches zero. Squadron Agents process incoming orders by sending a working part from inventory, if inventory available, or sending the order upstream to a depot when no parts in inventory. Also, a broken part will be fixed at the squadron with a specified percentage. Depots process incoming orders by sending a working part from inventory, if inventory available, or sending the order upstream to an Original Equipment Manufacturer (OEM). However, OEMs are not explicitly modeled, so extra time is added to the orders travel time to simulate an order being sent upstream, processed at an OEM, and returning downstream. Refer to Appendix B for further agent behavior details.

Model inputs are shipment times, repair times, mean time to failure, probability of fixing a part, initial inventory levels, and number of agents. Shipment time is the time to ship parts or send orders from one destination to another, which includes the time to process the order once it arrives. Repair time is the time to repair a part at either the squadron or depot. Mean time to failure is the time from a part becoming operational to the time it will fail. For this model shipment times and repair times are deterministic, while mean time to failure is stochastic. Probability of fixing a part corresponds to the percentage of broken parts that are sent upstream to be fixed, both at the squadron level and depot level. The model employs a base-stock inventory policy, so when a part is taken from inventory a replenishment order is immediately placed. Thus, the initial inventory level not only specifies how many parts are on hand at the start of a simulation run, but specifies how much will theoretically be in the system throughout the run. Since, the model is coded to run with any number of agents, the number of each type of agent

can be specified by the user. Input values used for analysis runs were randomly selected. That is, real data was not used to determine representative input values.

Model outputs are aircraft availability, customer wait time, and number of backorders. Aircraft availability is the "percentage of a fleet's total active inventory that is available (Mission Capable) for mission accomplishment," which is calculated by the equation below (GLSC 2008). Customer wait-time is a "pipeline measurement of customer due-outs expressed in days measuring the average time between issuance of a warfighter order and receipt," and backorders "measures the number of demands placed on the supply system that cannot be immediately satisfied from existing inventory (GLSC 2008)."

$$AA = \frac{Mission\ Capable\ Hours}{Total\ Hours} \times 100$$

One model assumption is incoming orders have a First-In-First-Out (FIFO) policy. Also, one time step in the simulation represents one day and the model simulates one year, or 365 days. For each time step the order of agent behavior execution is order agents, part agents, squadron agents, depot agents, and then plane agents. Spatial orientation is not considered in this model.

An agent-based model of this type can be used to augment strategic, tactical and operational decisions. Questions such as how much to order, when to order, how much inventory to hold, and what policy to implement for repairing parts at different levels in the supply chain.

5.2. Analysis

Two experiments were performed with the model described above. The first experiment considered how initial inventory levels affect system performance. To analyze this, initial inventory at squadrons was varied from 1 to 9 of each part at each squadron, while initial inventory at depots was fixed at 5 parts of each type at each depot. Five replications were run to obtain the average and standard deviation for aircraft availability, wait time, and number of backorders.

From **Figure 21**, 3, and 4 it can be seen that increasing initial inventory at squadrons improves aircraft availability, wait time, and number of backorders (Refer to Appendix C for numerical values). Increasing the initial inventory at squadrons from 1 to 5 increases average aircraft availability from 32.59% to 68.13% (109% increase), reduces average wait time from 9.93 days to 2.88 days (80% decrease), and reduces average number of backorders per year from 316.8 to 91.8 (71% decrease). By increasing initial inventory at squadrons from 5 to 9, average aircraft availability increases from 68.13% to 75.96% (11% increase), reduces average wait time from 2.88 days to 2 days (30% decrease), and reduces average number of backorders per year from 91.8 to 0.2 (100% decrease). The asymptotic trend in aircraft availability shows that it is not beneficial to have more than 7 parts in initial inventory because marginal increase in aircraft availability is essentially zero. For average wait time and average number of backorders, the asymptotic trend arises because inventory levels become large enough to satisfy all orders. Thus, there are no backorders and the wait time becomes the time to get the part from inventory and install it on the plane, which for this model is 2 days. The curves reach the asymptotes around 9 parts because the model only simulates 10 planes per

squadron, thus there can only be 10 broken parts of a single type corresponding to each squadron at any time.

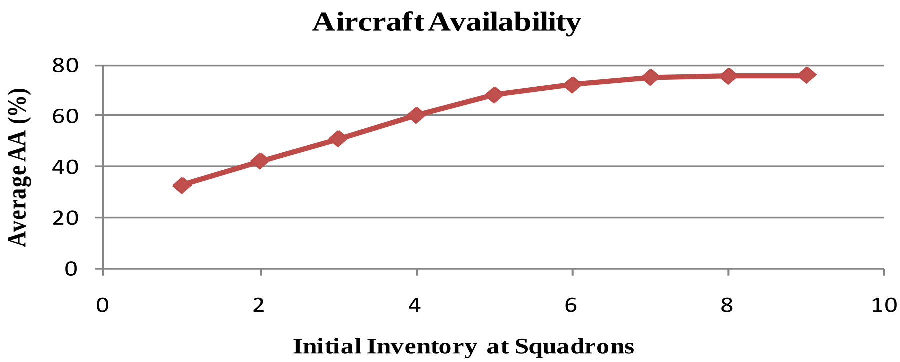


Figure 21 - Aircraft Availability for various inventory levels

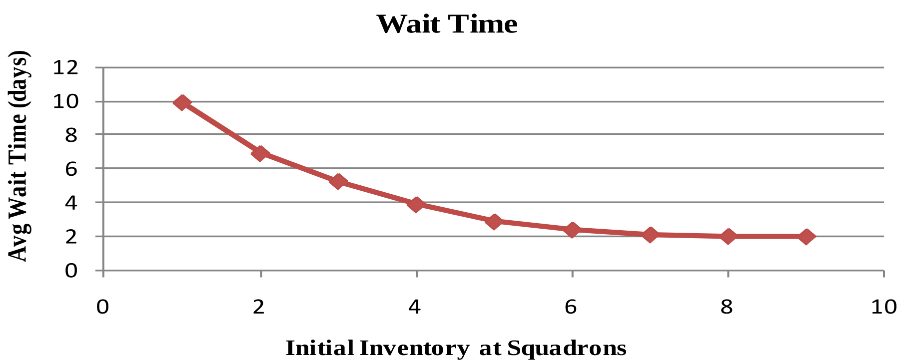


Figure 22 - Wait Time for various inventory levels

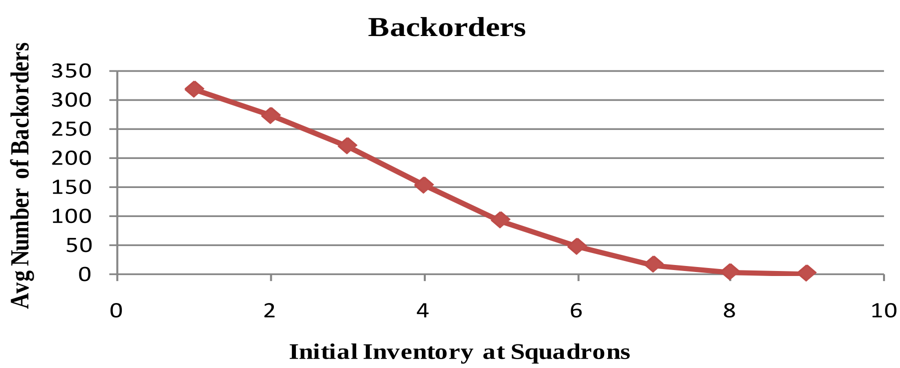


Figure 23 - Backorder levels for various inventory levels

The second experiment assesses the affect of fixing more parts at each squadron, rather than sending the parts upstream. This was done by varying the percentage of parts fixed at each squadron from 30% to 70%. Increasing the percentage of parts at each squadron could reflect an increase in personnel allocated to repairs or simply a change in

operational policy. Initial inventory levels were fixed at 3 parts per squadron and 5 parts per depot. Again, five replications were run to provide averages and standard deviations for the three output measures.

From Figures 5, 6, and 7 it is clear that increasing the percentage of parts repaired at squadrons improves aircraft availability, wait time, and number of backorders (Refer to Appendix C for numerical values). Increasing the percentage from 30% to 50% results in a 21% increase, from 43.23% to 52.48%, in average aircraft availability, a 25% decrease, from 6.69 days to 4.99 days, in average wait time, and a 15% decrease, from 250.8 to 212, in average number of backorders. Furthermore, increasing the percentage of parts fixed at squadrons from 50% to 70% results in a 17% increase, from 52.48% to 61.47%, in average aircraft availability, a 27% decrease, from 4.99 days to 3.63 days, in average wait time, and a 30% decrease, from 212 to 147.4, in average number of backorders. These results are less dramatic than those found with experiment one, but demonstrate the kind of analyses decision makers can perform throughout the Air Force supply chain to improve operations and cut costs.

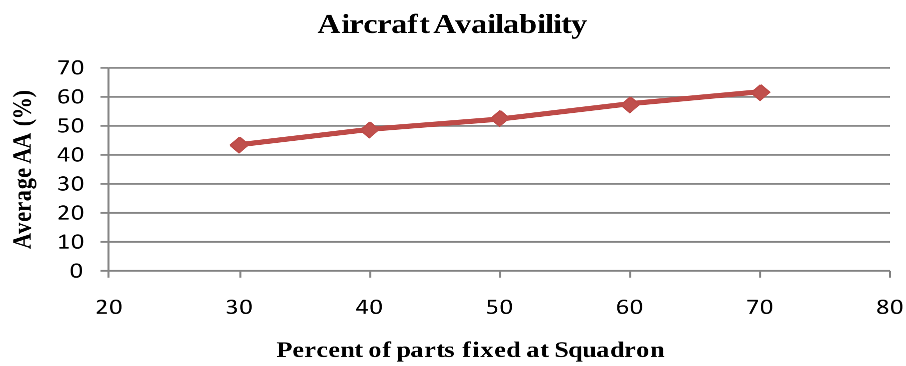


Figure 24 - Aircraft Availability for various squadron fix percentages

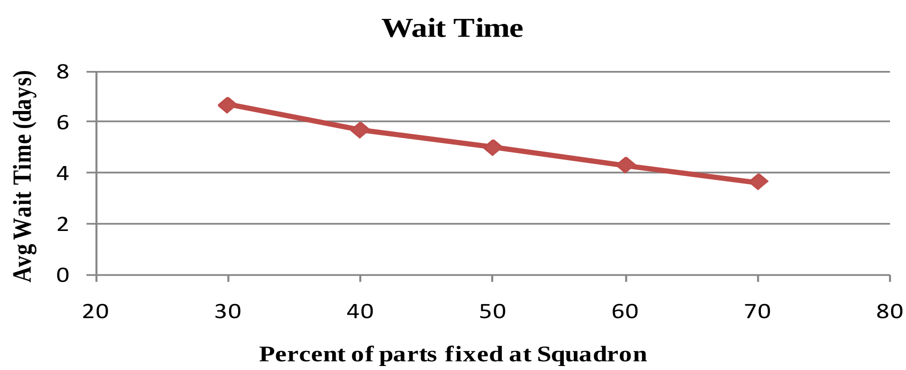


Figure 25 - Wait Time for various squadron fix percentages

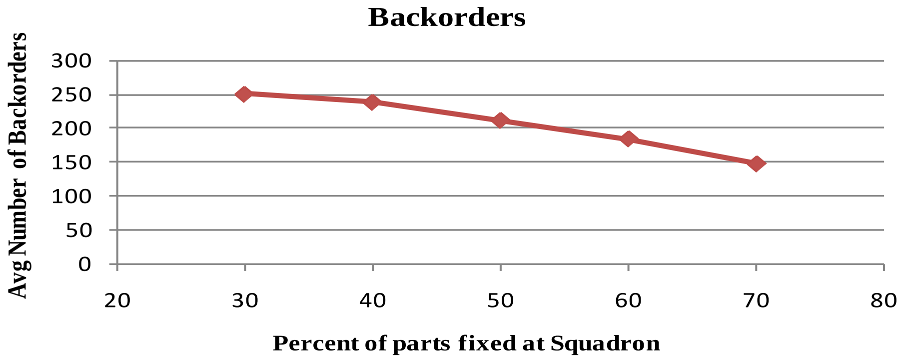


Figure 26 - Backorder levels for various squadron fix percentages

6. Conclusion

This paper presented background information on ABMS, ABMS for supply chain management, ABMS for inventory control, and an example agent-based simulation model for inventory control within the Air Force supply chain. Analysis of the simple inventory control model quantified average aircraft availability, average wait time, and average number of backorders for various inventory levels and policies for fixing parts at a squadron.

Further study with the supply chain model includes: adding more depots, squadrons, planes, and parts; employing stochastic shipment times and repair times; gathering and utilizing real data in the model; adding logic for cannibalization of aircraft; adding logic to consider maintenance personnel; adding original equipment manufacturer (OEM) agents; adding costs to the model; and adding optimization capability to the model.

References

AFGLSC. 2008 “Air Force Global Logistics Support Center Supply Chain Management Metrics Guide – Draft Copy.”

Amouzegar, M.A., R.S. Tripp, R.G. McGarvey, M.J. Neumann, D. George, and J. Cornuet. 2008. “Sense and Respond Combat Support: Command and Control-Based Approach.” *Air Force Journal of Logistics*, 31(4), 3-15.

Cao, H., F. Cheng, H. Xi, M. Ettl, S. Buckly, and C. Rodriguez. 2003. “A Simulation-Based Tool for Inventory Analysis In a Server Computer Manufacturing Environment.” *Proceedings of the 2003 Winter Simulation Conference*, 1313-1318.

Chen, D., Z. Zhou, and R. Hu. 2008. “Research on the inventory scheduling model based on agent-oriented Petri net in supply chain.” *Kybernetes*, vol. 37, no. 9/10, pp. 1234-1241.

Heath, B.L. 2010. *The History, Philosophy, and Practice of Agent-Based Modeling and the Development of the Conceptual Model for Simulation Diagram*. PhD Thesis. Wright State University, USA, 37-53.

Ito, T. and S. M. M. J. Abadi. 2002. “Agent-based material handling and inventory planning in warehouse.” *Journal of Intelligent Manufacturing*, 13, 201-210.

Jiang, C. and Z. Sheng. 2009. “Case-based reinforcement learning for dynamic inventory control in a multi-agent supply-chain system.” *Expert Systems with Applications*, vol. 36, pp. 6520-6526.

Jirong, W., L. Jun, Z. Yunhong, and H. Zongwu. 2008. “Simulation Study on Influences of Information Sharing to Supply Chain Inventory System Based on Multi-agent System.” *IEEE International Conference on Automation and Logistics*, pp. 1001-1004.

Krishnamurthy, P., F. Khorrami, and D. Schoenwald. 2008. “Decentralized Inventory Control for Large-Scale Reverse Supply Chains: A Computationally Tractable Approach.” *IEEE Transactions on systems, man, and cybernetics*. Vol. 38, no. 4, pp. 551-561.

Li, W., and C. Li. 2008. “Transshipment Policy Research of Multi-Location Inventory System Based on Multi-Agent System,” *IEEE International Conference on Automation and Logistics*. pp. 1344-1351.

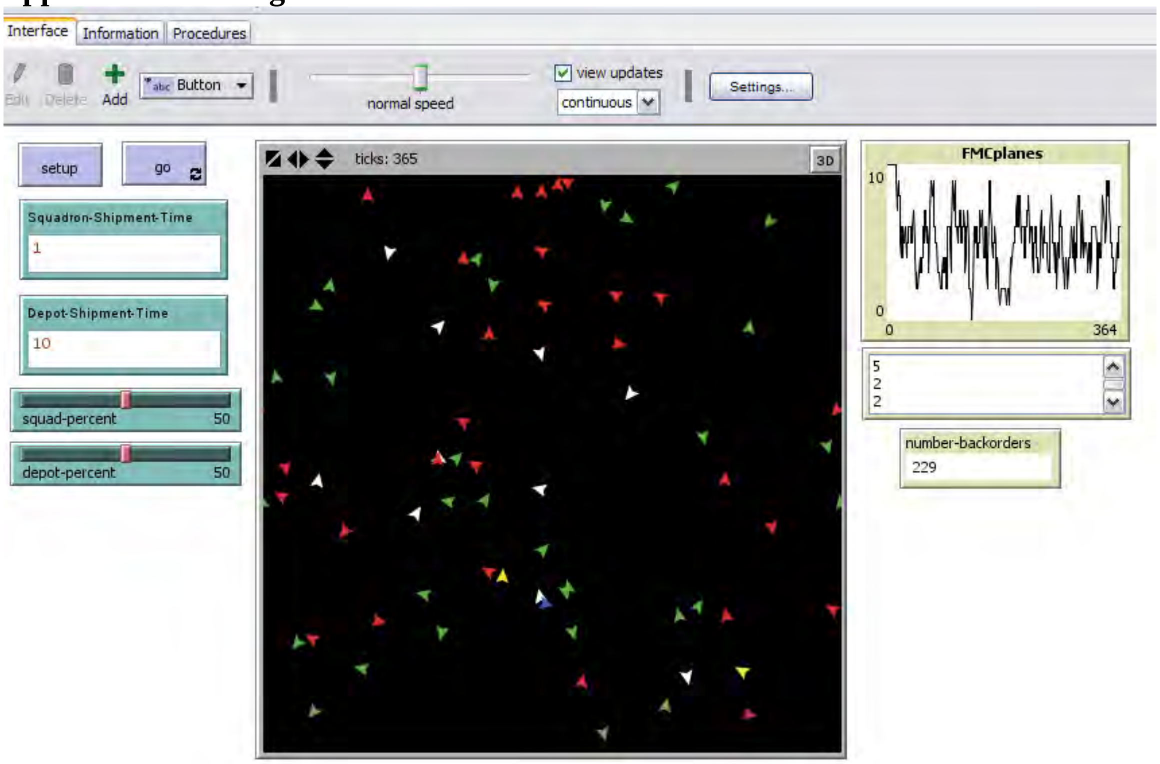
North, M.J. and C.M. Macal. 2007. *Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling and Simulation.* Oxford University Press: Oxford, NY.

Pan, A., S.Y.S. Leung, K.L. Moon, and K.W. Yeung. 2009. “Optimal reorder decision-making in the agent-based apparel supply chain.” *Expert Systems with Applications*, 36, 8571-8581.

Sirivunnabood, S. and S. Kumara. 2009. “Comparison of Mitigation Strategies for Supplier Risks: a Multi Agent-Based Simulation Approach.” *IEEE/INFORMS International Conference on Service Operations, Logistics and Informatics*, 388-393.

Thadakamalla, H.P., U.N. Raghavan, S. Kumara, and R. Albert. 2004. “Survivability of Multiagent-Based Supply Networks: A Topological Perspective.” *IEEE Intelligent Systems*, 19(5), 24-31.

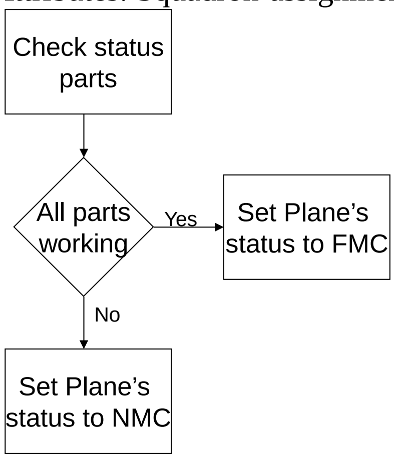
Appendix A – Netlogo Model



Appendix B – Agent Behavior Flowcharts

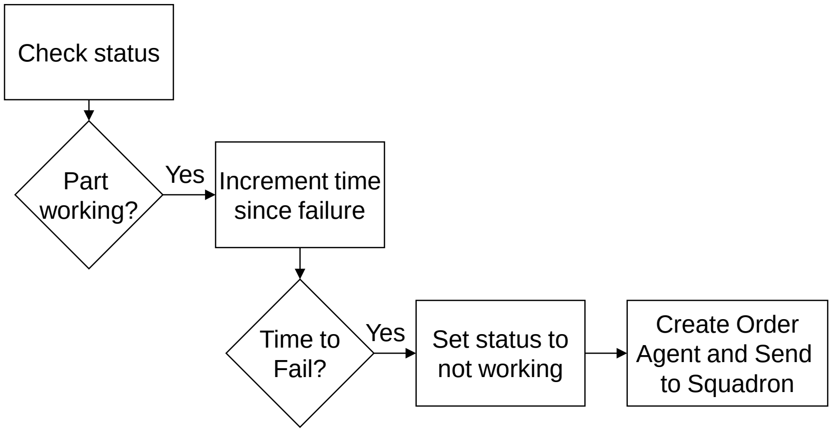
Plane Agents

Attributes: Squadron-assignment, operational status, parts-list



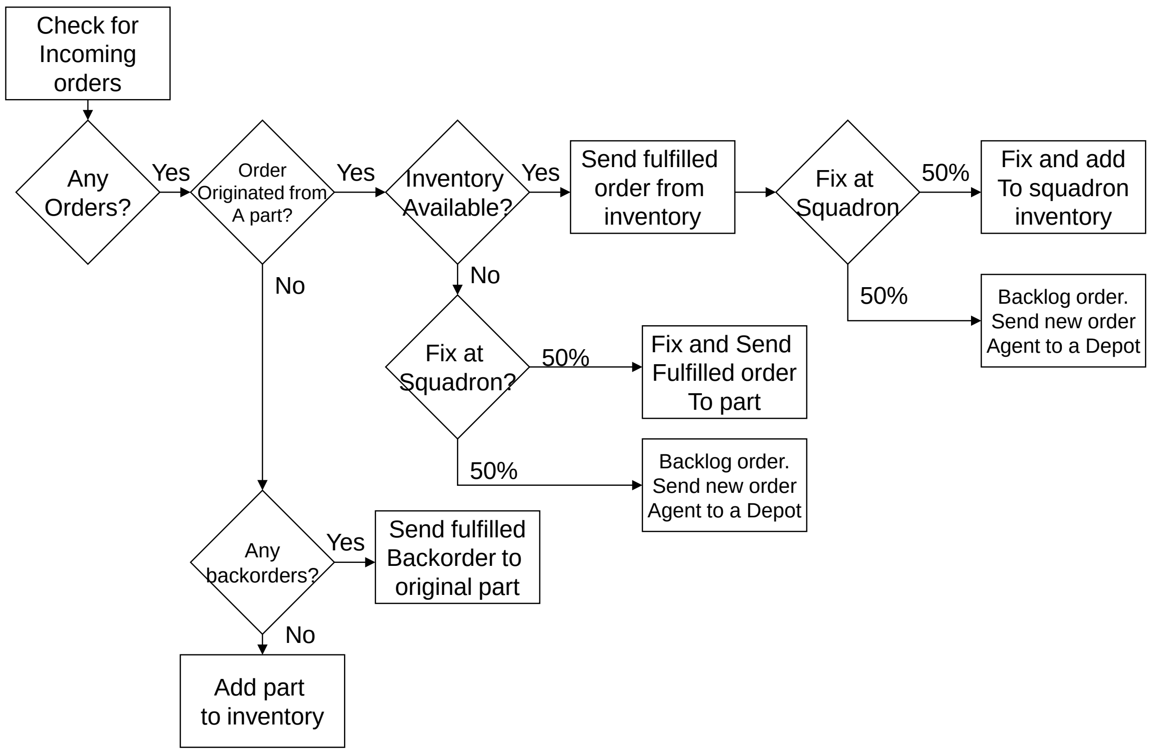
Part Agents

Attributes: Part-type, Squadron-assignment, Operational Status, Fail-time-count, Fail-time



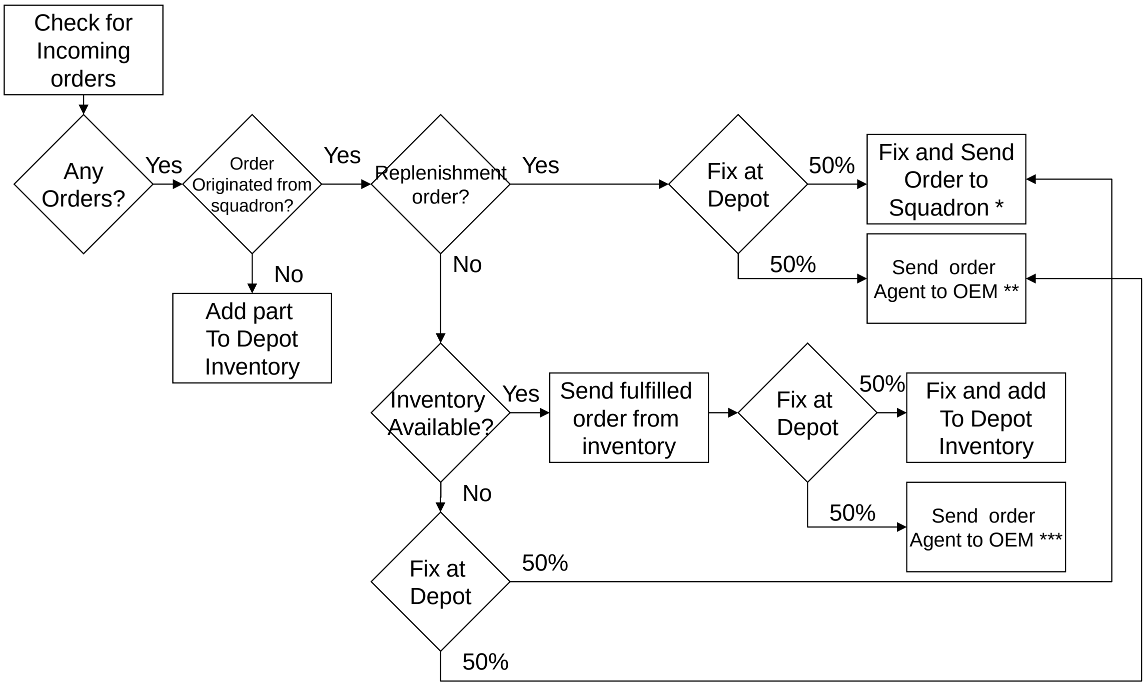
Squadron Agents

Attributes: Inventory, Backorders-list, Orders-list



Depot Agents

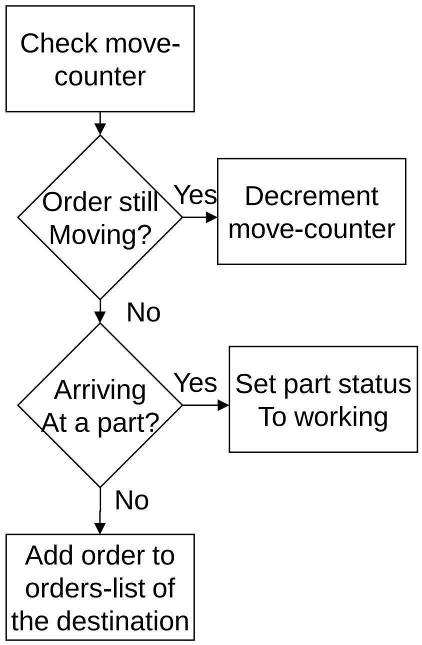
Attributes: Inventory, Orders-list



*Send order to Squadron with extra time added to simulate delay of fixing part at Depot
**Send order to Squadron with extra time added to simulate delay to get new part from OEM
***Send order to Depot with delay to simulate time to get new part from OEM

Order Agents

Attributes: Start-time, Part-type, Replenishment, Move-counter, Origin, Destination



Appendix C – Experimental output

Experiment 1

Initial Inventory		Number of Backorders		AA		Wait Time	
Squadrons	Depots	Average	St Dev	Average	St Dev	Average	St Dev
1	5	316.8	4.604345773	32.591781	1.1538769	9.9259173	0.4339925
2	5	271.4	5.770615219	42.257534	1.5792804	6.9156861	0.2713614
3	5	219.4	4.669047012	50.991781	0.7896402	5.267217	0.2038324
4	5	151.6	12.0124935	60.164384	2.3439473	3.8921871	0.2329282
5	5	91.8	11.62755348	68.136986	1.4751332	2.8797948	0.1512348
6	5	46.2	13.04607221	72.09863	1.0041386	2.4010044	0.11448
7	5	15.6	4.393176527	75.09589	0.4505996	2.1137316	0.0411724
8	5	2.4	0.894427191	75.517808	0.3279671	2.0209263	0.0097711
9	5	0.2	0.447213595	75.961644	0.3987219	2	0

Experiment 2

% fixed at Squadron	Number of Backorders		AA		Wait Time	
	Average	St Dev	Average	St Dev	Average	St Dev
30	250.8	8.899438185	43.232877	1.1461096	6.6931239	0.2740749
40	238.8	5.118593557	48.493151	1.1864943	5.6952877	0.23015
50	212	9.300537619	52.476712	0.7566804	4.9954466	0.1660229
60	184.6	12.68069399	57.227397	2.0286372	4.2982014	0.289476
70	147.4	12.50199984	61.473973	1.1523797	3.6321675	0.1747528

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14. ABSTRACT
This research develops a flexible agent based modeling and simulation (ABMS) framework for supply chain risk management with significant enhancements to standard ABMS methods and supply chain risk modeling. Our framework starts with the use of software agents to gather and process input data for use in our simulation model. For our simulation model we extend an existing mathematical framework for discrete event simulation (DES) to ABMS and then implement the concepts of variable resolution modeling from the DES domain to ABMS and provide further guidelines for aggregation and disaggregation of supply chain models. Existing supply chain risk management research focuses on consumable item supply chains. Since the AF supply chain contains many reparable items, we fill this gap with our risk metrics framework designed for reparable item supply chains, which have greater complexity than consumable item supply chains. We present new metrics, along with existing metrics, in a framework for reparable item supply chain risk management and discuss aggregation and disaggregation of metrics for use with our variable resolution modeling.

15. SUBJECT TERMS
Agent Based Modeling and Simulation, Software Agents, Variable Resolution, Risk Metrics

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